

Fall 12-2013

## **A Geographical Approach for Integrating Belief Networks and Geographic Information Sciences to Probabilistically Predict River Depth**

Nathan Lee Hopper  
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The University of Southern Mississippi

A GEOGRAPHICAL APPROACH FOR INTEGRATING  
BELIEF NETWORKS AND GEOGRAPHIC INFORMATION SCIENCES  
TO PROBABILISTICALLY PREDICT RIVER DEPTH

by

Nathan Lee Hopper

Abstract of a Dissertation  
Submitted to the Graduate School  
of The University of Southern Mississippi  
in Partial Fulfillment of the Requirements  
for the Degree of Doctor of Philosophy

December 2013

ABSTRACT

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by Nathan Lee Hopper

December 2013

Geography is, traditionally, a discipline dedicated to answering complex spatial questions. Although spatial statistical techniques, such as weighted regressions and weighted overlay analyses, are commonplace within geographical sciences, probabilistic reasoning, and uncertainty analyses are not typical. For example, belief networks are statistically robust and computationally powerful, but are not strongly integrated into geographic information systems. This is one of the reasons that belief networks have not been more widely utilized within the environmental sciences community. Geography's traditional method of delivering information through maps provides a mechanism for conveying probabilities and uncertainties to decision makers in a clear, concise manner. This study will couple probabilistic methods with Geographic Information Sciences (GISc), resulting in a practical decision system framework. While the methods for building the decision system in this study are focused on the identification of environmental navigation hazards, the decision system framework concept is not bound by this study and can be applied to other complex environmental questions.

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December 2013

## ACKNOWLEDGMENTS

The writer would like to thank the dissertation director, Dr. George Raber, and the other committee members, Dr. Carl Reece, Clifton Dixon, Gregory Carter, and Todd Holland for their advice and support throughout the duration of this project. I would especially like to thank Dr. Todd Holland for his patience and willingness to share, debate, and contribute to this body of work. His commitment and access to specific equipment and expertise is what allowed for this study to be conducted and completed.

Special thanks go to Dr. Margret Palmsten of the Naval Research Laboratory (NRL) for her experience and hard work training and executing of Bayesian networks and to Steven Spansel, formally of NRL, and Mr. David Lalejini for our many discussions. Appreciation must also be expressed to Miss Stephanie Ellis for her hard work and dedication to the review of the content and structure of this paper.

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## CHAPTER I

### INTRODUCTION

The main goal for modeling is to understand how assumptions, parameters, and variations in the input data can affect the results and conclusions drawn from them (Maguire, Batty, & Goodchild, 2005). Any dataset is only a representation of reality, and therefore contains uncertainty about the nature of the real work being represented (De, Goodchild, & Longley, 2007). “All models are wrong, we make tentative assumptions about the real world which we know are false but which we believe may be useful” (Box, 1979, p. 1). However, uncertainty about data can be integrated with the model by using a probabilistic framework. Interpreting the output probabilistically can be extremely useful for decision making and, therefore, decision systems (Maguire et al., 2005).

Traditional deterministic modeling cannot provide the sophisticated spatial analytics required to model uncertainty within the natural environment. Therefore, a probabilistic approach is best suited for scenarios such as resource allocation, quantitative risk analysis, error propagation, and decision making (Maguire et al., 2005). Interpretation of the probability information into a useful decision aid can be challenging and will require creativity (Maguire et al., 2005). The construction of a framework provides a platform in which information is created and presented so that the conveyance of probability information is understandable and useful as a decision aid in a controlled repeatable manner.

Multiple disciplines and various methods need to be assembled within a common workflow to create a decision framework. Each component within the framework could stand alone; however, by coupling Geographic Information Sciences (GISc) and remote

sensing techniques with a probabilistic prediction engine, a defined framework emerges as a robust and flexible decision system.

The probabilistic engine must analyze a series of variables that represent real-world attributes, each containing several unique states (Hicks & Pierce, 2009). This complex relationship between variables and their unique states allows for an intelligent belief network (also known as Bayesian networks, Bayes networks, or causal probabilistic networks) (Hicks & Pierce, 2009) approach to be applied to this issue. Belief networks (BNs) are designed to handle a large number of input variables, network relationships, and influences that are coupled into the overall probability prediction (Aguilera, Fernández, Fernández, Rumí, & Salmerón, 2011). The relationship between variables and states allows the BN to *learn* and continually refine the association involving the attributes and the existence of the various states by using conditional probabilities (Hicks & Pierce, 2009). This learning capability allows BNs to be utilized as predictors in a decision system.

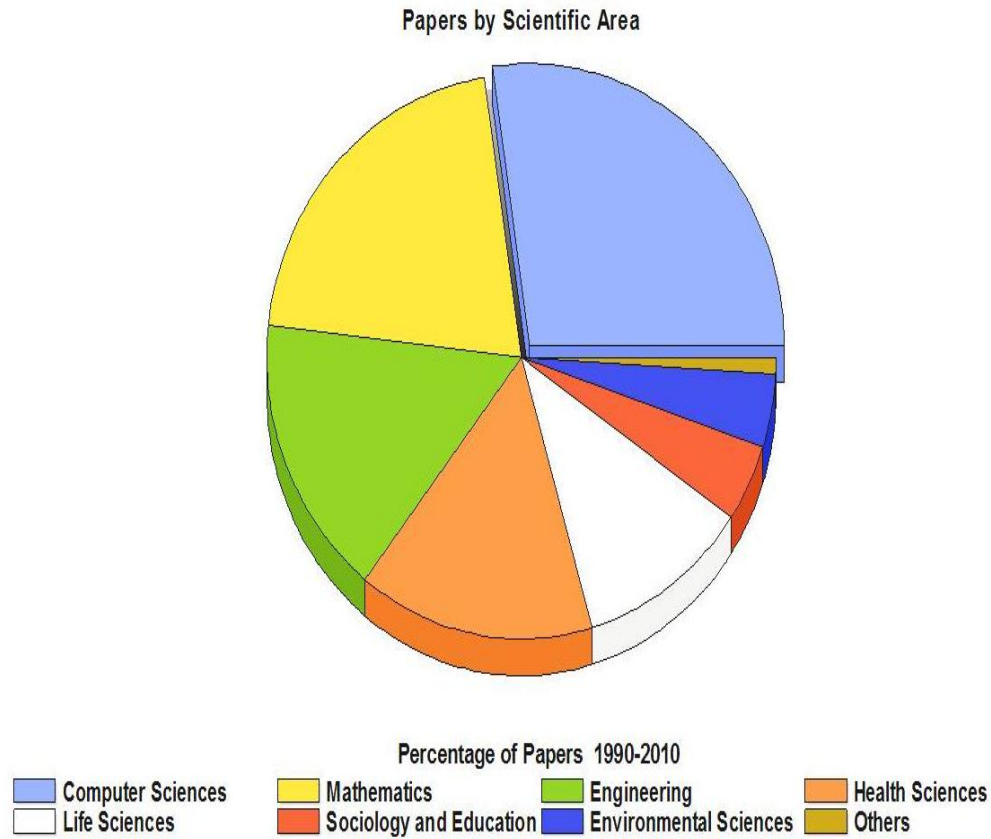
One of the computational powers of BNs is the propagation of new probabilities through inference based on Bayes' Theorem (Spansel, 2011). Bayesian inference uses the Bayes' Theorem to infer knowledge about variables in the network without direct knowledge about that variable (Spansel, 2011). The ability to compute posterior probabilities through node relationships is one of the most interesting features of BNs (Aguilera et al., 2011). This posterior probability calculation is referred to as inference, evidence propagation, or belief (Aguilera et al., 2011). Equation 1 illustrates the relationship between forecast and observation variables.

$$\frac{P(F_i|O_j) = P(O_j|F_i)P(F_i)}{P(O_j)}$$

*Equation 1.* Posterior probability calculation referred to as inference, evidence propagation, or belief. ***F*** = Forecast ***O*** = Observation ***i/j*** = Variables

In the last decade, BNs have been applied to various decision support systems in diverse areas to include medical diagnosis, safety assessment, forensics, procurement, equipment fault diagnosis, software quality, banking, and finance (Pourret, Naïm, & Marcot, 2008). Probabilistically representing the environment makes BNs an appropriate tool for modeling complex systems, since it can deal with uncertainty (Aguilera et al., 2011; Ghabayenm, McKee, & Kemblowski, 2004; Haapasaari & Karjalainen, 2010; Marcot, & Ellis, 2006; McCann, Wang, Robertson, & Haines, 2009; Rieman et al., 2001). Despite BN potential in environmental system applications, only 4.2% of publications between January 1990 and December 2010 came from the environmental science community; therefore, their potential is as yet largely unexploited (see Figure 1) (Aguilera et al., 2011).





*Figure 1.* Belief Network publications between 1990 and 2010 by scientific area where environmental sciences represents only 4.2% of publications (Aguilera et al., 2011).

A simplistic example of a BN would be to consider the event “grass is wet,” where grass is wet ( $W=\text{true}$ ) has two possible causes: either the sprinkler is on ( $S=\text{true}$ ) or it is raining ( $R=\text{true}$ ). The strength of this relationship is shown in Figure 2 in the wet grass table’s conditional probability distribution (Hujer, 2011).

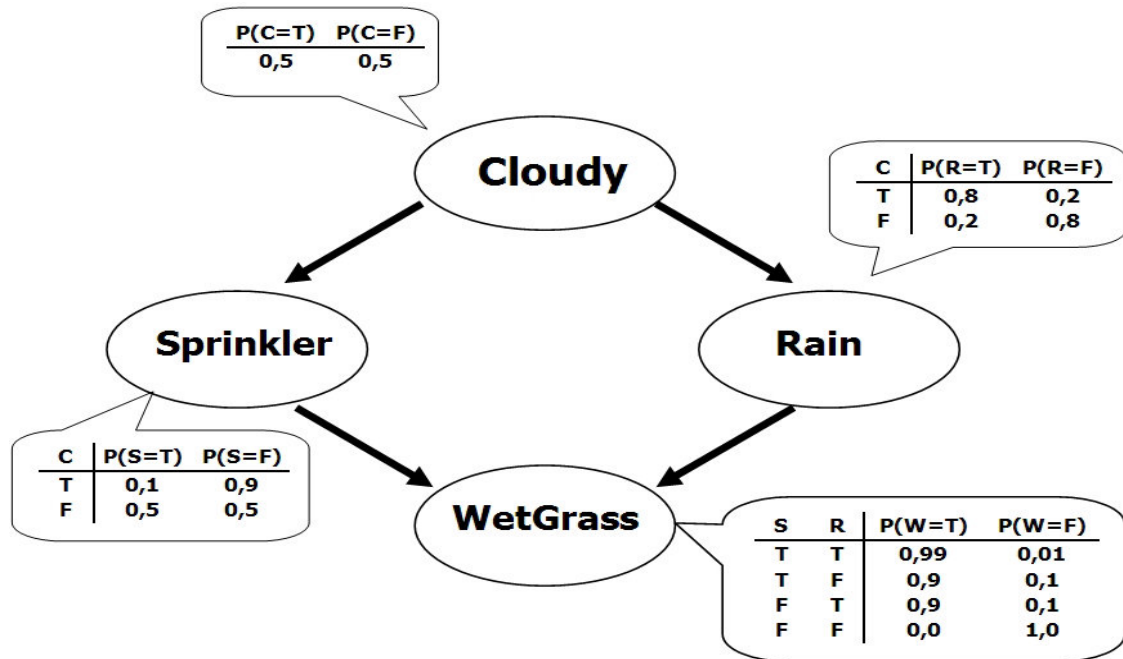


Figure 2. Wet grass network has two components: one qualitative and another quantitative. Directed acyclic graphic (DAG) represents the qualitative portion also referred to as the structure of the Bayesian network (Darwiche, 2009).

### Environmental Application

Approaching the fluvial system probabilistically allows for decision makers to analyze questions regarding navigation or river crossing operations that may be performed. Examples of applied questions that can be addressed using such a prediction method are “Is the river deeper than X meters at this specific point?” or “What area of this river system contains the highest probability of being able to successfully cross with X vehicle?”.

The physical relationship between the environmental variables of a river’s discharge, width, depth, and velocity is what allows a probabilistic model to be constructed. As river discharge increases so does the width, depth, and velocity. (Christopherson, 1997; Smith & Pavelsky, 2008). This relationship is expressed in

Equation 2 where  $Q$  = discharge,  $w$  = width,  $d$  = depth, and  $v$  = velocity (Christopherson, 1997).

$$Q = wdv$$

*Equation 2.* Relationship between river discharge, width, depth, and velocity.

By rearranging the variables in equation 2, the depth variable could be solved for, as shown in equation 3.

$$D = \frac{Q}{V \times W}$$

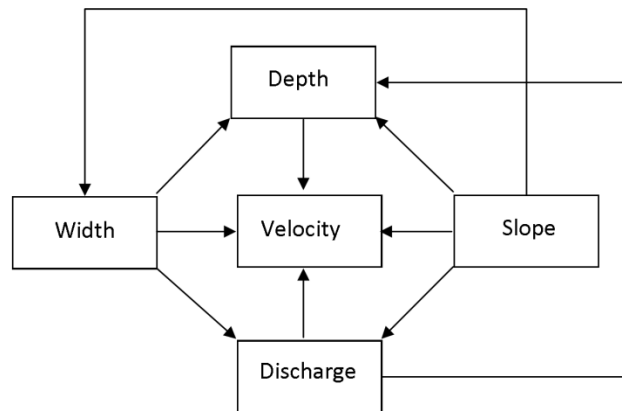
*Equation 3.* River depth equation.

Solving for  $D$  with variable values of  $Q = 80$  cubic m per second,  $v = 0.5$  m per second,  $w = 50$  m, and  $d = 3.2$  m. However, when uncertainties in those values are applied to calculate the depth parameter, then a decidedly different conclusion emerges. For instance, using  $Q = 80 \pm 15$  cubic m per second,  $v = 0.5 \pm 0.25$  m per second, and  $w = 50 \pm 10$  m, the depth then ranges between 1.4 and 9.5 m.

In developing countries, hydrologic data is seldom available due to economic, political, or proprietary reasons (Smith & Pavelsky, 2008). Therefore, a remote sensing (RS) approach is best applied to large, remote, data-sparse rivers (Smith & Pavelsky, 2008). Even where reliable monitoring networks are present, hydrologic conditions between stations are interpolated or at best modeled over large areas (Smith & Pavelsky, 2008). The ability to account for uncertainty in observations or environmental conditions makes BNs an appropriate tool for modeling river systems (Aguilera et al., 2011).

### Previous Research

A study by Palmsten, Holland, and Plant (2013) explored probabilistically predicting river velocity values using a BN. A BN is a way of describing the relationship between causes and effects of the environmental variables and is made up of nodes and arcs (Fenton & Neil, 2007). The collection of nodes and arcs is referred to as the graph of the BN, represented by Figure 3 and Figure 4. Each node of the graph has an associated probability table associated with it, referred to as a Node Probability Table (Figure 4) (Fenton & Neil 2007).



*Figure 3.* A schematic representation of Bayesian network used to predict river velocity (Palmsten et al., 2013).

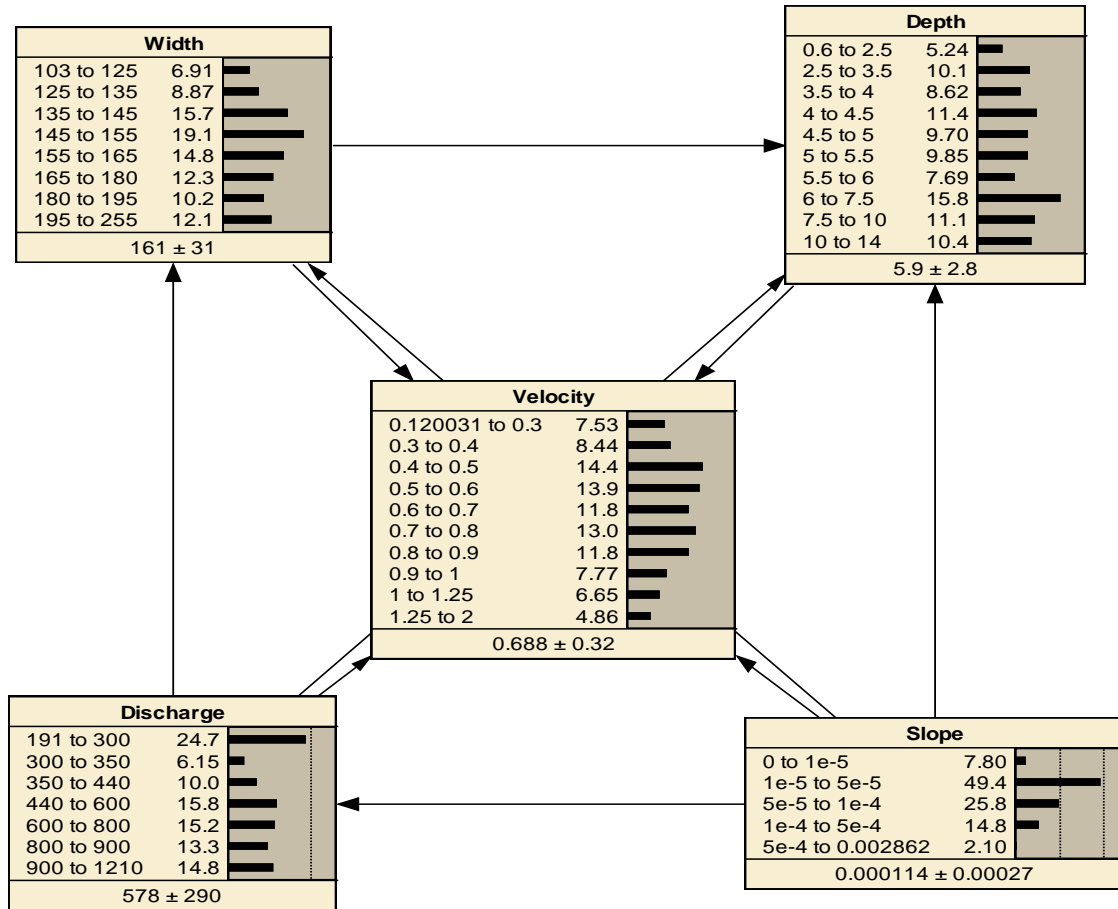


Figure 4. Palmsten et al., (2013) used Norsys Netica as the Bayesian statistical engine ([www.norsys.com](http://www.norsys.com)). Netica is a commonly used BN modeling software due to its graphical interface and intuitive outputs (Hicks & Pierce, 2009). This figure illustrates the Netica BN graphical model, displaying the mean and standard deviation for each variable below the distribution (Palmsten et al., 2013).

A BN must be trained with various circumstances prior to predicting any probabilistic outcomes. This supervised training is a critical step in ensuring the reliability of the prediction is realistic (Palmsten et al., 2013). The data sources used in this learning phase are often sizable and usually difficult to process. One of the common pitfalls of a BN is the allowance of any number of potential variables regardless of their existence of, origin of, or influence on the system's predictive ability (Palmsten et al., 2013).

The BN used for predicting river velocity probabilities was trained from 1999 Sites of USGS River Gaging Station, each with up to 10 years of observations. This resulted in 677,211 observations used in the training process, which included geomorphic characterizations such as slope, discharge, velocity, width, and depth (Palmsten et al., 2013). The relationship between river velocity and depth coupled with the extensive amount of training applied to the velocity BN made it applicable to this study.

Dr. Meg Palmsten of the Naval Research Laboratory created a later version of this network to include the variables of sinuosity and radius of curvature (Figure 5). Sinuosity is measured as a ratio of the distance between two points on the stream divided by the straight line distance between the two points (Figure 6). This ratio describes the shape of the fluvial system so that any sinuosity value greater than 1.5 is considered a meandering system (Ritter, 2012). Sinuosity is not the best measure of the shape, as it refers to the overall meander of the system but not of the bend curvature (Bridge, 2009). Therefore, the radius of curvature measure can be referred to in terms of symmetry of the bend; therefore, if the distance between points and the minimum radius of curvature is the same, then the bend is considered symmetrical in nature and otherwise has an asymmetrical shape (Figure 7) (Bridge, 2009).

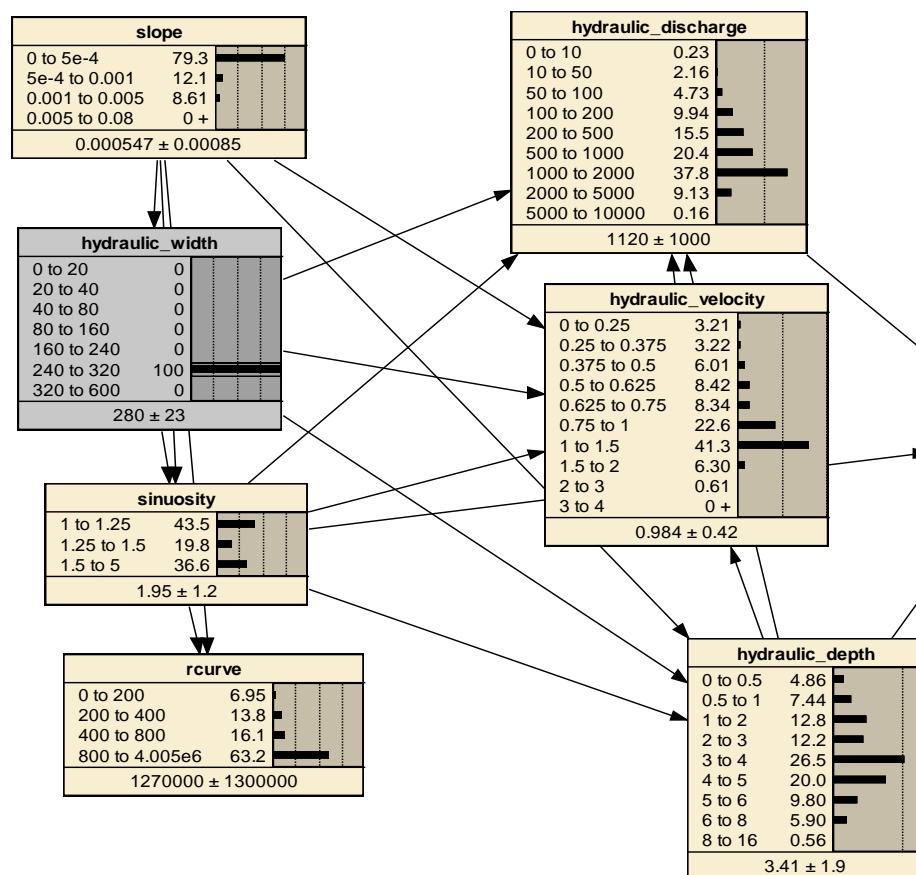


Figure 5. Dr. Palmsten's latest version of the BN containing the relationship of river variables. The hydraulic width variable in this DAG demonstrates the ability to query the network directly and derive depth probabilities, which are displayed in the depth table. By selecting the 240 to 320 bin, the probability that depth will be between 3-4 is 26.5% (Palmsten et al., 2013).

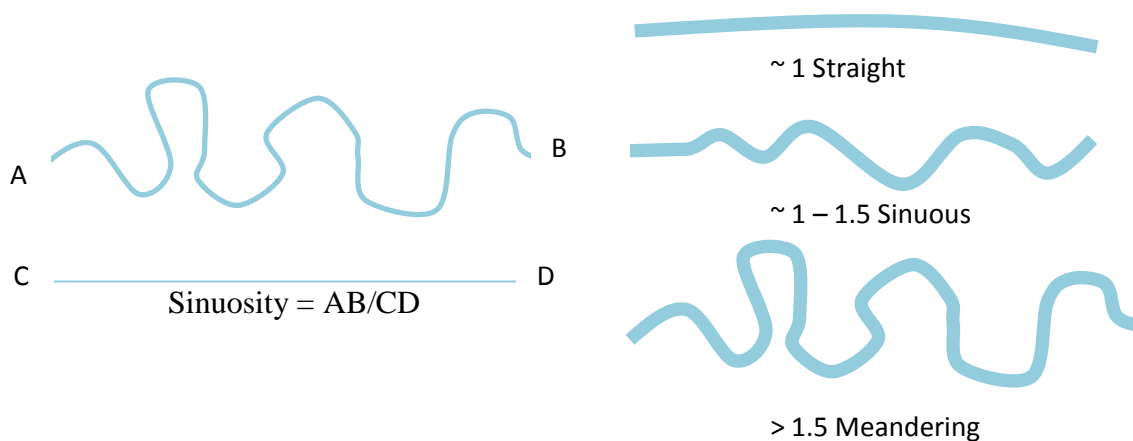
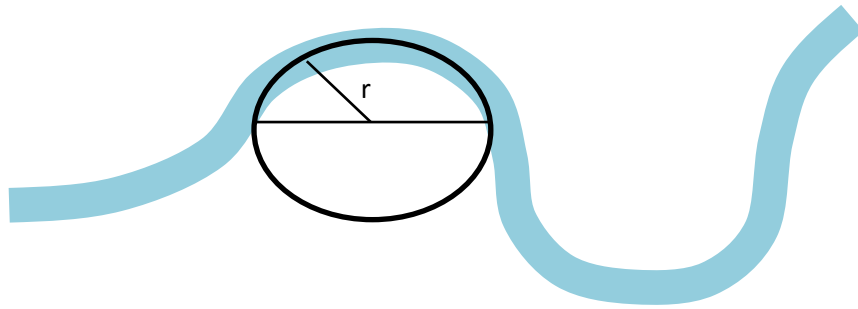


Figure 6. Sinuosity ratio (Allen, 1970).



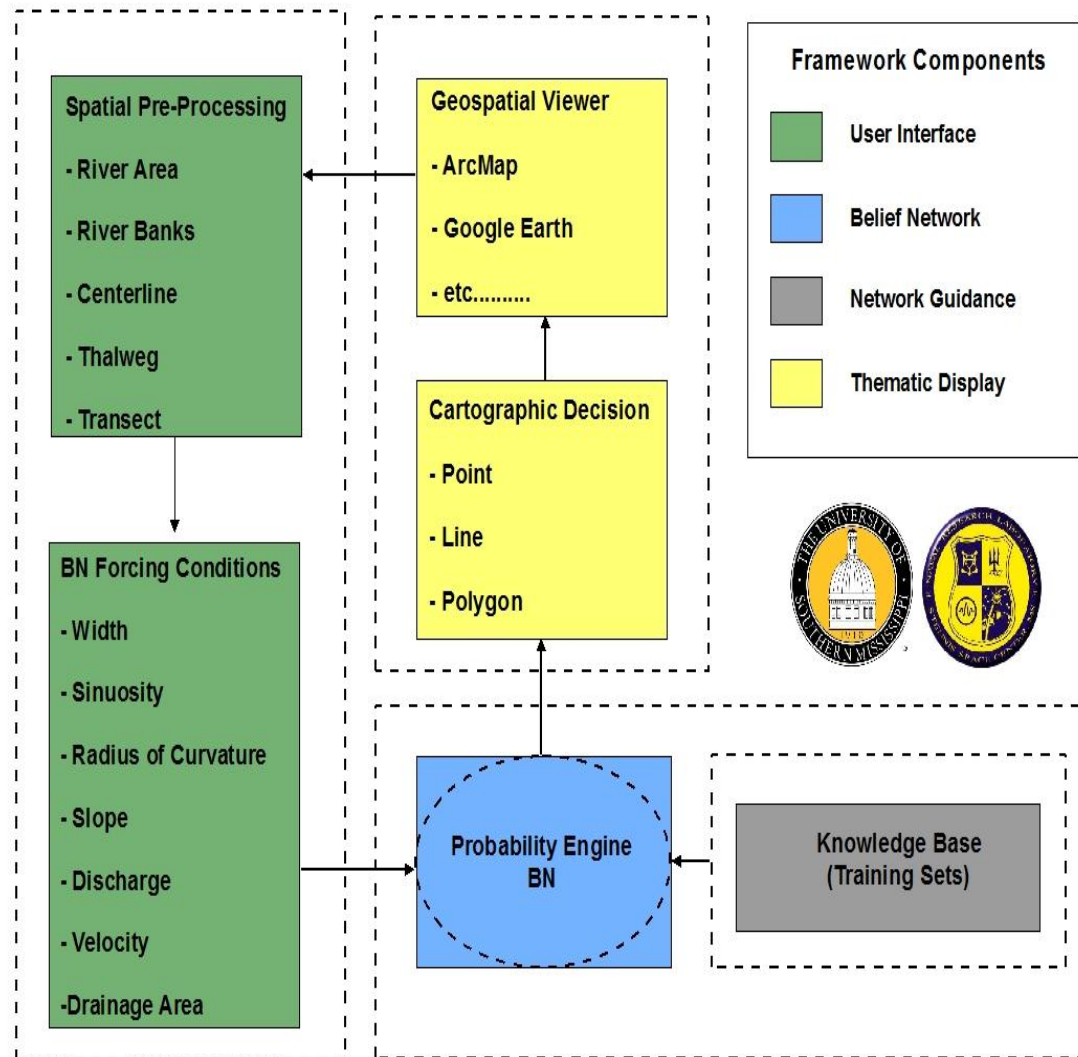
*Figure 7.* Radius of curvature of a river bend (Bridge, 2009). Radius is represented by “r.”

Although velocity is a probabilistic factor of the BN, the subject of this study is concentrated on the depth prediction aspect of the BN. However, all processes and methods for the decision system to predict a probability of depth may also be applied to velocity specific questions.

The objective of this study is to design a decision system framework that utilizes GISc, RS, and BNs to produce geospatially-enabled information as an aid for decision makers. The focus of this framework will be in the analysis of the riverine environment as it pertains to the safety of navigation aspect of the river (Figure 8).



### River Navigability Potential Framework



*Figure 8.* River navigability potential framework. This system consists of three main components that are linked together to function as one framework. The user interface contains preprocessing steps necessary to derive constraint variables for the BN. The BN is a trained belief network that executes probability predictions and, finally, a thematic or cartographic visualization component to aid in displaying probabilistic values.

## Decision System Framework

The decision system framework contains methods and procedures to spatially derive forcing conditions from imagery using RS techniques inside of a geographic information system (GIS) that requires the execution of BN. Dr. Palmsten's trained BN was utilized in this study as the probabilistic prediction engine portion of the decision system (Palmsten et al., 2013). For additional information on this BN, see "Velocity Estimations Using Bayesian Network in a Critical-Habitat Reach of the Kootenai River, ID" by Meg Palmsten, K. Todd Holland, and Nathaniel Plant (2013).

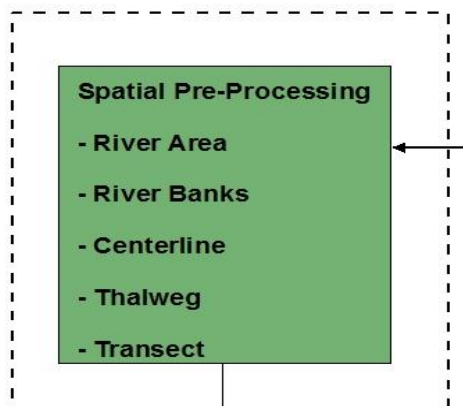
The framework contains cartographic components for presenting the probabilistic information in a spatial context. As a result, a structure and process for creating a decision system that solves complex spatial questions in the riverine environment has been created (see Figure 8). The following chapters will discuss the relationship between GISc, RS, and BN and the challenges associated with building the framework for these components to function as a viable decision system.

## CHAPTER II

### METHODS

#### Spatial Preprocessing

An important component to the framework design is the preprocessing of spatial information. The wetted area, banks, islands, centerline, and transects are essential features that allow for other physical conditions to be calculated (Figure 9). Although manual feature extraction techniques, such as *heads up digitizing* are sufficient for generating these features, the process can be highly inefficient and tedious depending on the spatial area and the river morphology (Jensen, 2007). Therefore, a semi-automated approach to streamline the process was designed and implemented inside the framework.



*Figure 9.* The preprocessing component of the river framework. As with most processing methods within a GIS, there are numerous ways to achieve a desired result. The preprocessing component contains only the methods applied in this study.

Applying spatial analytical techniques such as image classification, filters, and raster to vector conversion provides the base tools and principals to achieve this semi-automated feature extraction process (De et al., 2007). Deriving the wetted river area feature from imagery is an essential component to this study, since the centerline, river banks, and island features can be derived from the wetted area.

### *Wetted Area*

Automatically identifying water pixels from remotely-sensed imagery is the first requirement for a semi-automated workflow. One method for water identification is pixel classification, either through supervised or unsupervised techniques. The main difference in these two spectral classifying algorithms is that supervised requires a training step before classification occurs, while unsupervised aggregates the natural spectral groupings into classes before the analyst determines land cover (Lillesand & Kiefer, 2000).

Another method for water pixel identification is Normalized Difference Water Index (NDWI), which is a ratio between spectral bands of a multispectral (Ji, Zhang, & Wylie, 2009, p. 1307). Equation 4 expresses this ratio between two bands of a multispectral image and enhances the spectral response patterns by contrasting between the different spectral regions while canceling a large portion of the noise component of these bands (Ji et al., 2009, p. 1307). The ability of this ratio to determine water pixels is highly dependent on the characteristics of absorption that water has on the Near Infrared (NIR) portion of the electromagnetic spectrum (Jensen, 2007). Three methods were developed to provide flexibility in the application of this research, as no two remotely-sensed images are exactly the same (Lillesand & Kiefer, 2000).

$$NDWI = (Green - NIR)/(Green + NIR)$$

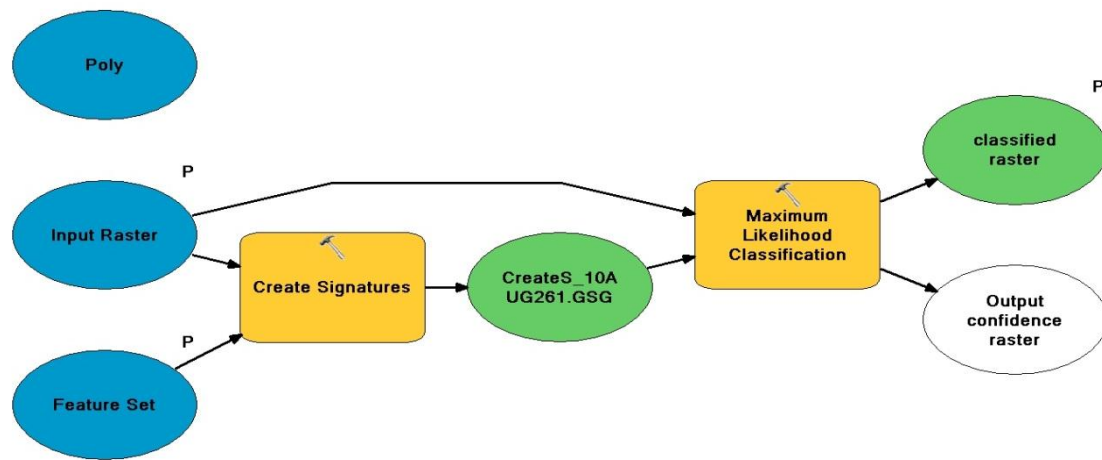
*Equation 4.* Normalized Difference Water Index (NDWI). Green and NIR are the reflectance of green and NIR bands of a multispectral image. The NDWI value ranges from -1 to 1 with a threshold of 0 therefore any values > 0 represents water and any values  $\leq 0$  represents land cover.

These three types of water identification methods was developed into tools through ArcGIS modelbuilder and designed to be executed in ArcMap's table of contents

(Figures 10 and 11). These tools and techniques were designed to be flexible and executed by a varying level of experienced users producing the features required by the forcing conditions component of the framework.



*Figure 10.* ArcGIS tool box with different custom workflows for image classification. This session-based geoprocessing workflow enables one of the most flexible and efficient workflows within the ArcGIS framework and reduces the need for intermediate data to be written to disk (Allen, 2011).

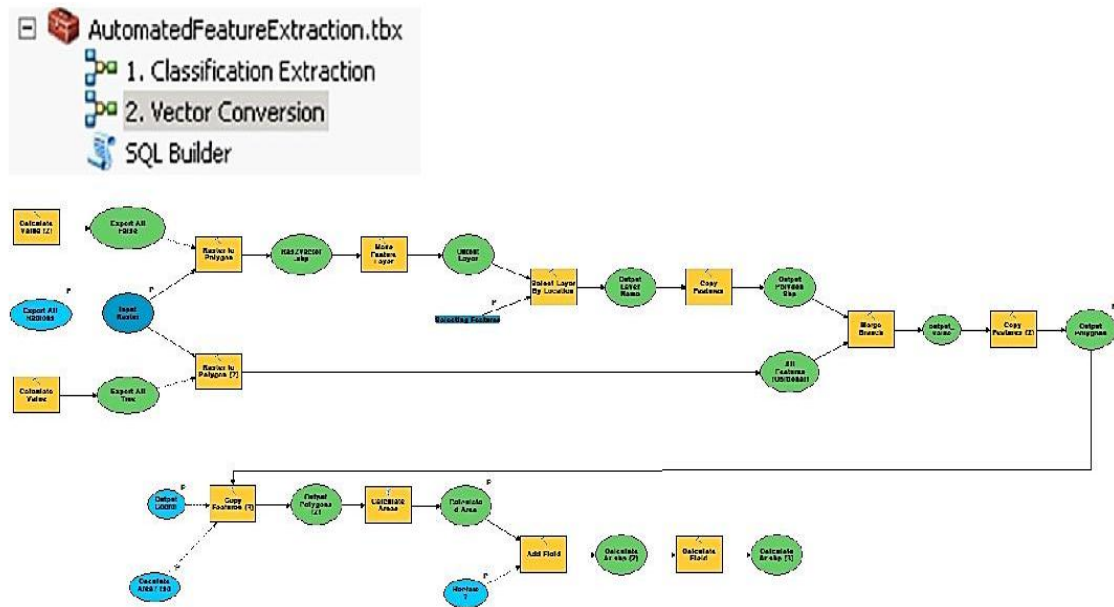


*Figure 11.* Supervised classification geoprocessing workflow example.

Once a suitable classification has been reached, the classification extraction step of the geoprocessing workflow can begin (Figure 12). This model contains several important steps in the preprocessing methodologies before vector conversion can occur that most other processes ignore. The raster passes through several filters, such as a majority, low pass, and boundary clean. These filters are designed to reduce the noise that may be present within the classification due to image noise and the classification process



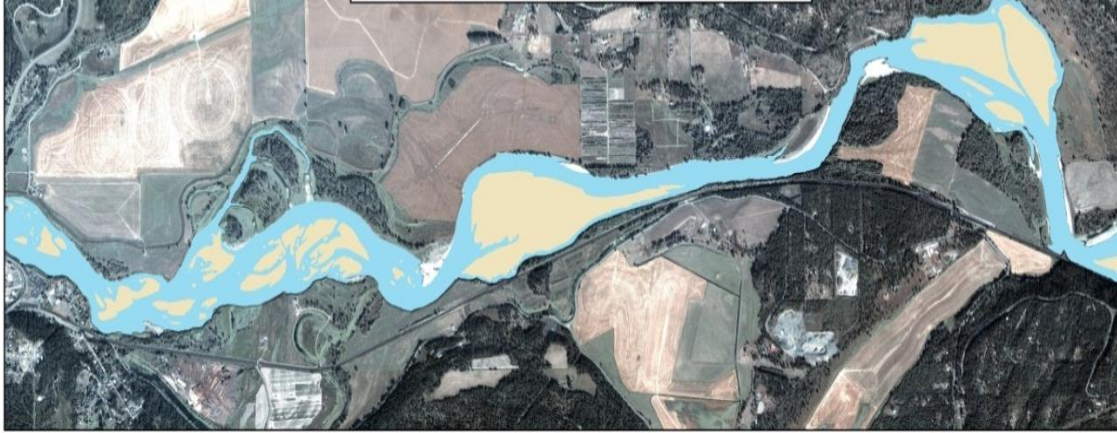
to connect the two in a seamless environment provides a powerful capability for the geoprocessing framework to answer complex spatial problems (Allen, 2011) (Figure 13).



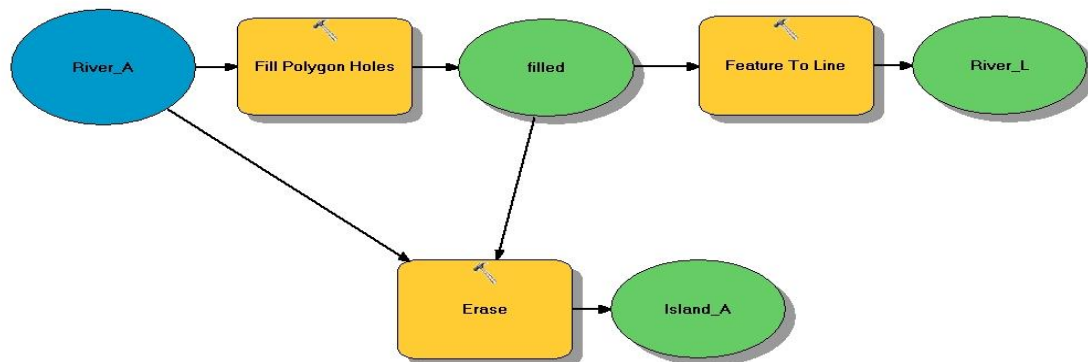
*Figure 13.* ArcGIS toolbox containing the classification extraction and vector conversion geoprocessing models. In model building, the same principals apply as in coding; it is always recommended to build things in blocks for testing purposes. Then, refine the models trying to combine as many steps and make the workflow as seamless as possible.

Once the river area has been derived the next process in the workflow is to execute the island extraction and river bank generation process (Figure 14). This process is only necessary if the intended study area has an island present and the island geometries are a desired output, as they are not needed for the prediction engine. This automated process produces the island by taking the river polygon as an input and executes an ET Geowizard fill polygon holes function, resulting in a wetted bank-to-bank polygon representation of the river area. This filled polygon is erased with the original river area, producing a new feature of river islands and converting the wetted area polygon to polyline to create a left bank and right bank line feature (Figure 15).





*Figure 14.* Map displaying the geoprocessing results. The tan polygon areas represent the island areas of the extraction process. Kootenai River, Idaho.



*Figure 15.* Geoprocessing tool for island extraction utilizing the fill polygon holes tool from ET Geowizard. ET Geowizard is a third party extension for ArcGIS and can be downloaded for free from [www.ian-ko.com](http://www.ian-ko.com).

### *Spectral Analysis*

The spectral response of a river is a complex relationship between suspended sediment load, surface roughness, and bottom morphology (Lillesand & Kiefer, 2000). However, water does provide some useful characteristics when observed by a remote sensor. The two most interesting of these in terms of water depth or bottom shape is the absorption in the Near infrared (NIR) portion of the spectrum and a higher transmittance is the green portion of the visible spectrum (Lillesand & Kiefer, 2000). By applying a



simple ratio of the red band to the green band of a multispectral image, a relative depth map can be produced (Equation 5).

$$\text{Red Band} / \text{Green Band} = \text{RG Ratio}$$

Equation 5. Red Green Ratio.

The two extracted raster surfaces have to be converted to floating point before conducting the raster math. However, with the use of the raster calculator tool in ArcGIS, this float conversion can be achieved when executing the core mathematical operation (Figure 16). The initial ratio raster contains a great deal of noise therefore; a Low Pass Filter was applied to reduce this effect (Figure 16).

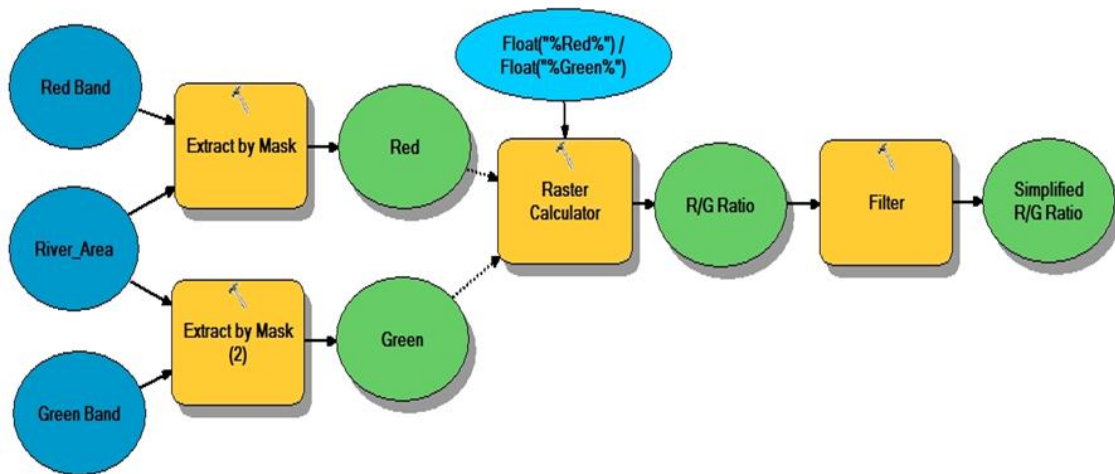
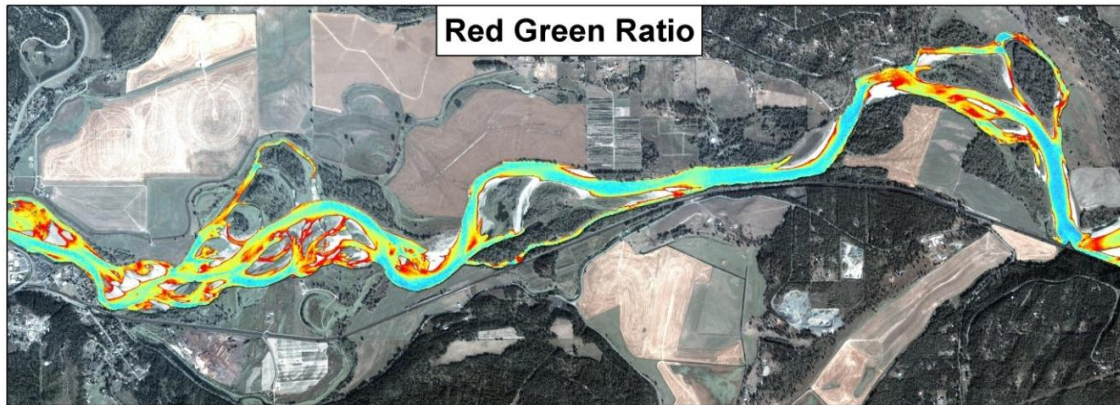


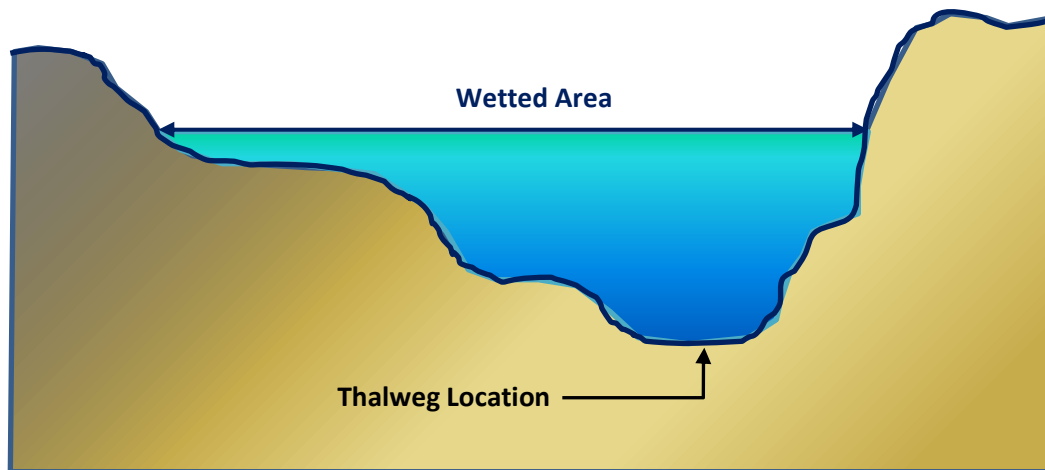
Figure 16. Geoprocessing model that applies the red/green ratio and filtration to the output raster. Performing an extraction by mask from both bands of the image using the river polygon significantly reduces the amount of processing time required to conduct the ratio calculation.

Applying a red to blue color stretched render with a histogram stretch of 2 produced an engaging image where red areas represent shallower depths and blue areas represent deeper depths (Figure 17). This technique does not attempt to predict depth values in any way, but is merely a way of representing the deeper portions of the river in

a qualitative manner. The deepest portion of a fluvial system that has the greatest velocity is referred to as thalweg location (Strahler & Strahler, 1994) (Figure 18).



*Figure 17.* Red/green ratio where blue tones of the ratio are relatively deeper than the red tones of the ratio.



*Figure 18.* Thalweg or deepest point along a transect.

Although the band ratio is not a direct environmental constraint variable, it is a valuable tool for delineate the thalweg's spatial location. The ratio information indicating the thalweg location can be used by subject matter experts to spatially adjust the automated centerline feature to where the most probable depth should be located.

### *Centerline*

The wetted area polygon allows for the automated processing to create a centerline feature. However, centerlines still proved to be the most difficult of features to derive without asking the user to collect the feature manually. Three methods were researched, designed, and tested to achieve an automated centerline feature extraction process.

First was the use of ET Geowizards for ArcGIS desktop, which has a function for creating centerlines included in the software. The results produced a centerline, but with angular geometries representing the bends in the river (Figure 19). Smoothing operations were applied, but resulted in the centerline leaving the spatial constraint of the original wetted area polygon. Transects produced from this centerline had gross geometric inaccuracies, and therefore did not provide an authentic representation of the true river width at that transect location.

**ET Geowizard**

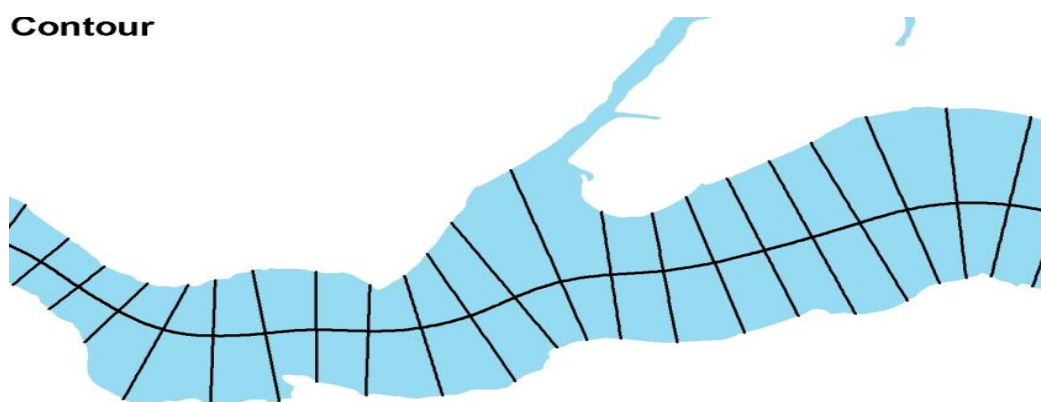


*Figure 19.* Results of the transect creation tool utilizing the centerline derived from ET Geowizard.

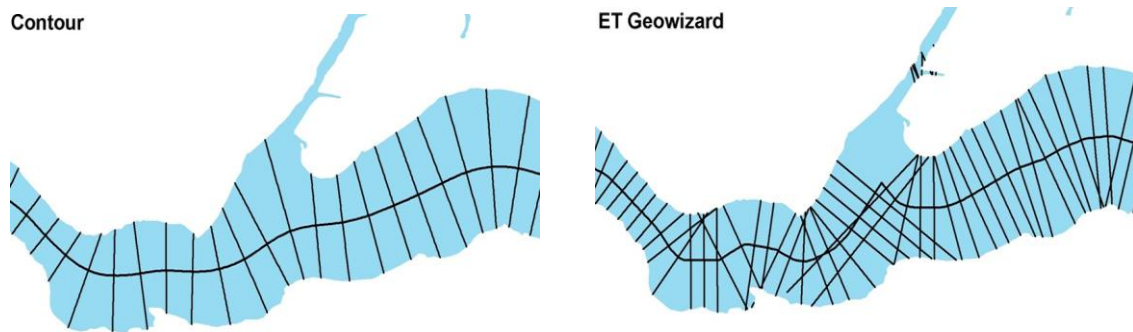
Second was the use of thiessen polygon analytic tools through ArcGIS's spatial analyst extension. Thiessen or proximity polygons create unique regions in which a unique x, y location may exist (De, et al., 2007). This method produced a better

centerline, but required a massive amount of editing by the user before it could be used to generate transects. The angularity of the river bends still remained a serious issue with this technique, although it did approximate the river bends better. Therefore, transects created from this method looked remarkably similar to Figure 19.

Third was the contouring of a raster surface through ArcGIS 3D analyst. Contouring a surface requires lines at different values to be treated as elevation representations. This was achieved by splitting the river bank lines created in the island extraction process step into left and right bank segments and assigning a value of 0 to the left bank and 1 to the right bank. Treating these lines as elevation contours allowed for the topo to raster tool to be executed producing an interpolated surface for the entire domain. Once the interpolation process was complete, a contour list tool from the ArcGIS spatial analyst was run to produce the 0.5 contour line. This process produced the best cartographic and analytical representation of the river centerline. Contour operations was the most simplistic approach, yet yielded the best geometric representation of the river centerline (Figure 20 and 21).



*Figure 20.* Map containing the results of the transect creation tool utilizing the contour centerline method.



*Figure 21.* Comparison between contouring and ET Geowizard centerline techniques.

### *Transects*

Transects could be created manually, as the centerline has now been established; however, this process would be laborious and increase the likelihood of over or under sampling an area. Therefore, an automated process that contains the transect creation was included in the framework to minimize this risk and streamline several processing steps required for the BN forcing conditions components of the framework.

The centerline provides the ability to automate the creation of evenly spaced transects by spatially selecting nodes at a specified distance (10, 50, or 100 m) and calculating the 90 degree angle in which a transect line is established. The required inputs for transect creation are the wetted area, centerline, and transect spacing. The spacing is decided upon by the user and previous examination of the fluvial system in question. This study applied a constant transect spacing of 100 meters for development, testing, and execution of the framework. The centerline transect creation process was developed using the python scripting language, but could have easily been integrated into a geoprocessing workflow to support more complex workflows.

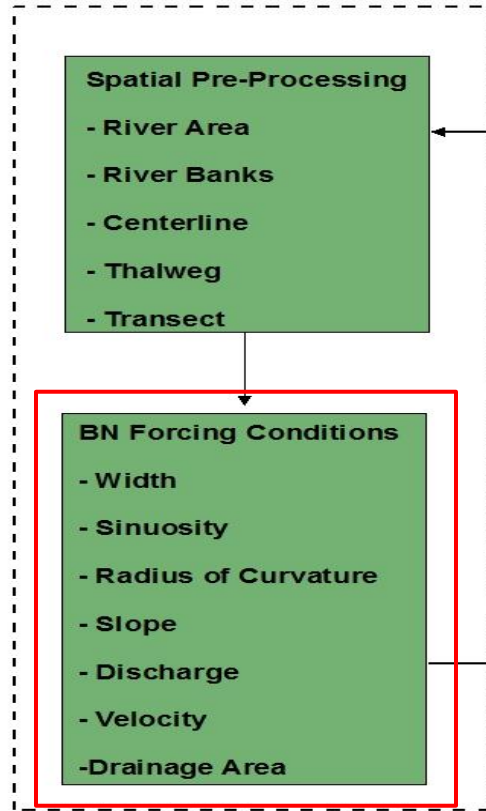
### BN Forcing Conditions

The spatial preprocessing component of the framework has created a river centerline and transects that will be utilized in the calculation of environmental variables, also referred to as forcing conditions for the BN. The BN requires the forcing conditions of river width, sinuosity, radius of curvature, slope, discharge, velocity, and drainage area to execute probabilistic depth predictions (Table 1). The following sections will discuss how each of these variables are created and where they are stored before being passed to the BN and how that information is passed to the BN within the framework (Figure 22).

Table 1

*Listing of the Fluvial Forcing Conditions and Source for the BN*

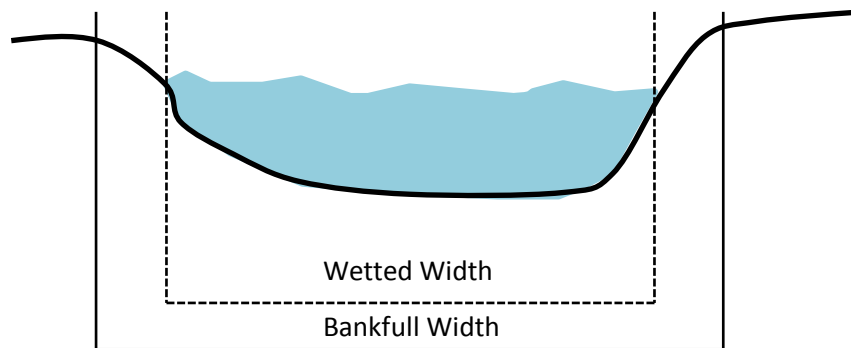
River Variables	Source
Width	Transect
Sinuosity	River Centerline
Radius of Curvature	River Centerline
Slope	Subject Matter Expert/Digital Elevation Model (DEM)
Discharge	Observations/Subject Matter Expert (SME)
Velocity	Observations/Subject Matter Expert (SME)
Drainage Area	Subject Matter Expert/Digital Elevation Model (DEM)



*Figure 22.* BN forcing conditions component of the framework. The red box indicates the component.

### *Width*

The RS community has treated the two-dimensional measurements as equivalent to the one-dimensional variables such as width, depth, and velocity of a classical gauge station (Smith & Pavelsky, 2008). However, with passive RS systems, the wetted area or width is the variable of choice (Smith & Pavelsky, 2008) (Figure 23). Strong correlations between remotely-sensed width variables and ground measurements of river discharge often taken at different temporal and spatial sampling makes RS a predictive tool that can aid in river forecasting (Smith & Pavelsky, 2008).



*Figure 23.* Wetted width comparison to bankfull width. Wetted width is a measurement of flow conditions at the time of sampling, usually under low flow conditions, while bankfull width is a measurement of high flow conditions. These parameters are used to characterize the hydrologic characteristics of a stream, where wetted width is used to calculate current discharge and bankfull width is used to estimate stream discharge under flood state conditions (Smith & Pavelsky, 2008).

The wetted width is calculated from the transect geometries created from the river centerline. Transects are extremely valuable to the research project due to the fact they hold the width parameter for the probability engine Netica to be able to make a probabilistic depth prediction.

#### *Sinuosity/Radius of Curvature*

The centerline is also used to calculate other important environmental forcing conditions such as sinuosity and radius of curvature. The same ability to link spatial processing steps in geoprocessing exists within python scripting and provides a flexible development and implementation environment to provide a streamlined user interface experience. The script creates transects and adds fields where calculations of the sinuosity, radius of curvature, and wetted width are stored. The wetted width is calculated from the transect geometry where the sinuosity and radius of curvature utilize the centerline to be calculated. Slope and drainage area fields are added in anticipation of



user interaction in the next processing step. After all of the necessary fields have been added and calculations conducted, the river polygon is used to clip the transect features to ensure that their spatial location falls inside the bounds of the river area.

#### *Slope/Drainage Area/Velocity/Discharge*

The inclusion of subject matter expert opinions and analysis allows for generalized forcing conditions to be applied in the BN. Regional values such as slope, drainage area, velocity, and discharge are calculated and stored within the transect attribute table. These values are estimates and are assigned a bin with uncertainty ranges based on the user's input. Although slope and drainage area variables could be calculated through GISc methods from a digital elevation model, this study applied known parameters for the study areas chosen. The python script that does a simple field calculation is meant to provide some constraint values to the transect attribute table when little ground samples exist, allowing the user to make broad observations about the fluvial system and categorize the constraints.

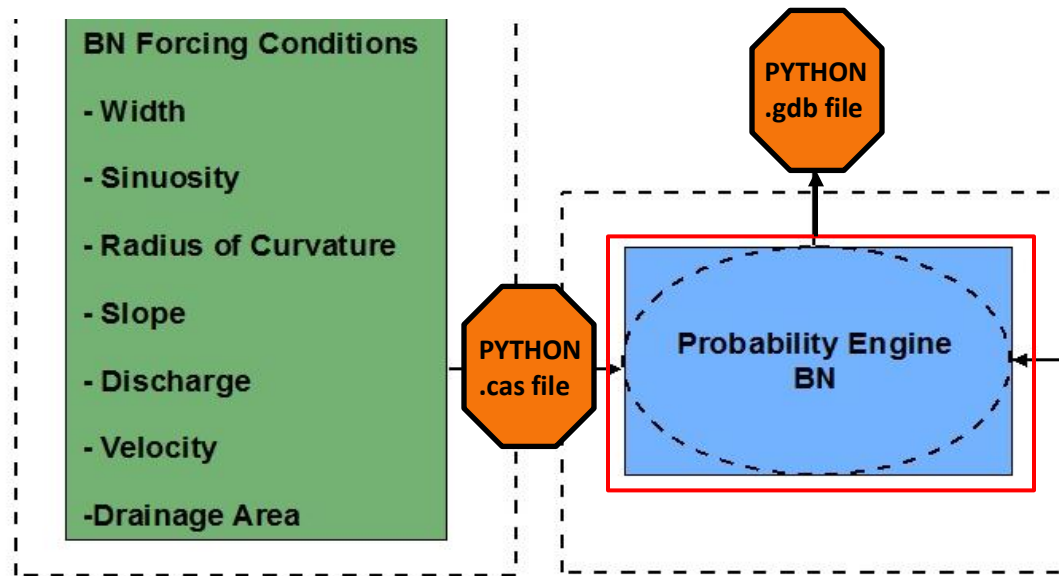
In some instances, some in situ velocity data may have been collected through observations or a remote device such as a drifter. A python script was used to include this information and apply it to the transect attribute table. This process takes a velocity's feature class with a velocity field the transect feature class and a distance value from transect as input. The distance is required because this value is used to calculate a distance buffer around transects in which the velocities will be averaged and assigned to the proper field inside transects attribute table. Caution should be taken in the arbitrarily assigning a distance value without considering the density spacing of the transect feature class. For instance, if a transect space of 10 m is applied and a search radius of 50 m is

chosen, then inaccurate velocity values will be returned and used in the probability calculation. The default value is set to 25 m and in most cases is a reasonable distance value to search, but if transect spacing is less than 25 m, then this value will need to be adjusted accordingly.

### Bayesian Network Execution

Once transects have been created and prepared with all the necessary constraint attributes, the information they contain must be delivered to the BN. However, GIS and the probability engine are not integrated systems and tools, and methods had to be developed to transfer information from the GIS to Netica for processing. This type of architecture is referred to as loosely coupled and is the most commonly used in the integration of GIS with probabilistic modeling (Maguire et al., 2005).

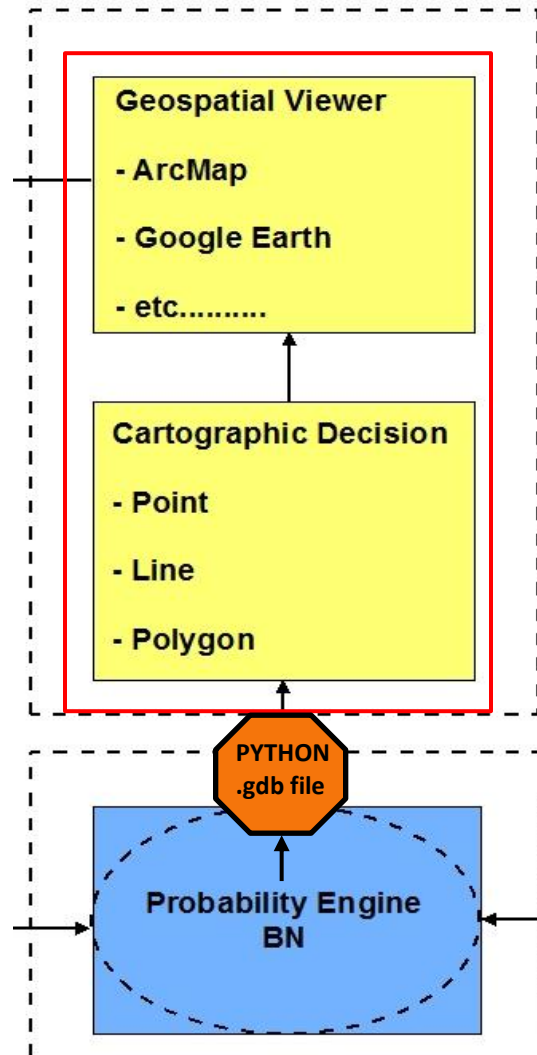
The transfer from a spatial domain where the preprocessing and forcing conditions have been created and calculated to a probabilistic one is handled through a python script. The process was designed to translate the spatial information contained in the transects into a formatted case file for Netica. The specific text-formatted file is placed in a directory where Netica can access and execute the BN probabilistic predictions using this case file as inputs for comparison to the trained network values (Figure 24).



*Figure 24.* Netica's BN and the execution of the probabilistic prediction. Integration of GIS and BN utilizing python's scripting language allowing for a loosely coupled architecture allowing the construction of the decision system framework.

### Cartographic Representation

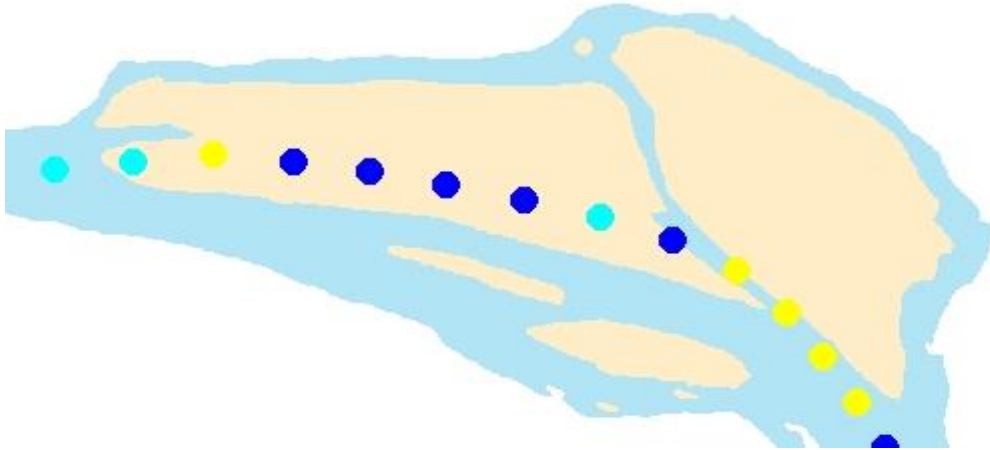
The BN execution returns as a probabilistic depth prediction containing an x, y location and requires translation back into a spatial format. This is achieved again through the use of a python script, where a point feature class is created from the center point of the original transects. Upon the feature class creation, all the necessary attribute fields required to hold the prediction results are added. Values of probability of at least some depth are added to those fields and calculated with probabilities. This processing results in a point feature class that is ready to be brought back into the GIS for more visualization-related processing (Figure 25).



*Figure 25.* The cartographic decision process coupled with the visualization software component of the framework.

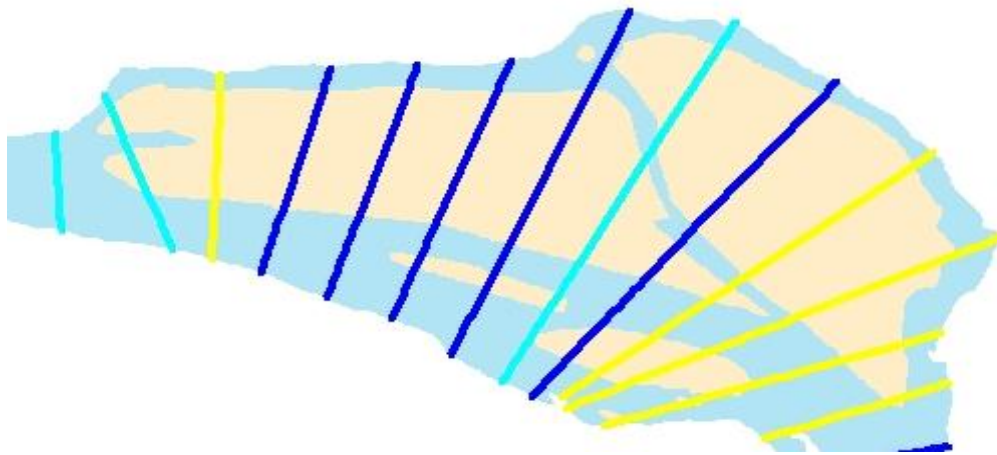
Representing probabilities cartographically presents unique challenges, such as the user's understanding of what a probability value indicates. Probability results from the BN are returned as a point feature representing the transect center x, y coordinate of the input transect. These points contain several probabilities, so the display is directly related to the question posed, for instance: "Is the river at least 2 m deep?" To present the answer to this question, one could simply use the classification render on the attribute column that represents the probability of at least 2 m (Figure 26). However, representing

the point geometry with a color opens the possibility of misinterpreting the point as a true depth sounding, as this is the way they are traditionally visualized. Depending on the centerline used to derived the original transect lines, the line center coordinate could be placed on a river island where there is no probability actually located (Figure 26).



*Figure 26.* Point representations of probability values. Kootenai River, ID.

Another cartographic option is to classify the transect lines directly displaying the probability information. This approach is better from a spatial perspective, however there is no consideration given to the location of islands or where the thalweg location is along that line (Figure 27).



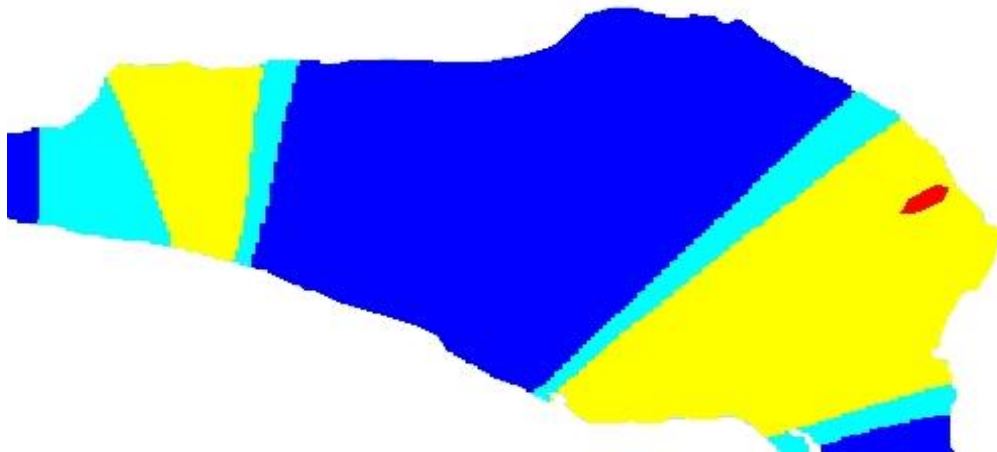
*Figure 27. Probability information displayed as line geometries. Kootenai River, ID.*

Although symbolized lines are more accurate spatially, the possibility of confusion still remains. Transects are simply a sample method that is designed to represent an area. Therefore, the most accurate way to portray this probability information is with a surface. This could be achieved through a raster or polygon representation.

To represent this probability information as a raster surface, there are several processing steps that must be taken. The first is to join the attributes from the probability results back to the original transect lines, making them probabilistically aware.

Densifying the line gives it evenly-spaced nodes; in this case, it was at a distance of every 10 m. This step allows for the interpolation algorithm to have more samples, producing a smoother result. The topo to raster tool was used to transform the lines into a surface representing the desired attribute probability of at least 2 m. The extract by mask function can be executed to extract the raster surface contained within the river polygon area.

Applying a graduating, color-stretched render with a bilinear interpolation display provides a cartographic, rich representation of the probability area between transects (Figure 28). Any conversion from a point or line geometry to a surface is done through interpolation methods, therefore the risk of altering the original probability predictions is always present.



*Figure 28.* Probabilistic information displayed as a raster surface. Kootenai River, ID.

However, this approach still poses spatial problems, such as displaying probability values over island areas, which could lead to less confidence in the probability and therefore negatively impact the final decision. This can be overcome in two ways one would be to Set Null the areas where islands are present the second would be to convert the raster to a polygon and erase the island areas. This process is best achieved by applying spatial analysis through a cartographic geoprocessing model (Figure 29). Displaying the final results to the user as polygon areas of probability with the highest spatial fidelity allows them to concentrate on and have confidence in the probability information (Figure 30).





northern Idaho and Belize River in Belize were chosen due to their unique climatic and geomorphological characteristics (Christopherson, 1997).

The Kootenai River originates just north of Kootenai National Park, located in British Columbia, Canada. The 485 miles of river meanders through the states of Montana and Idaho before returning to Canada and eventually ending at Kootenay Lake (Kootenai River Network, Inc., n.d.) (Figure 31). The river's surrounding topography is dominated by steep, mountainous country and drops nearly 5,914 feet in elevation as it flows through the basin (Kootenai River Network, Inc., n.d.). The severe drop in elevation coupled with the area's plentiful rainfall makes the Kootenai River the second largest tributary of the Columbia River system in terms of runoff volume and the uppermost major tributaries of the Columbia River, which is the largest North American river that empties into the Pacific Ocean (Knudson, 1994).

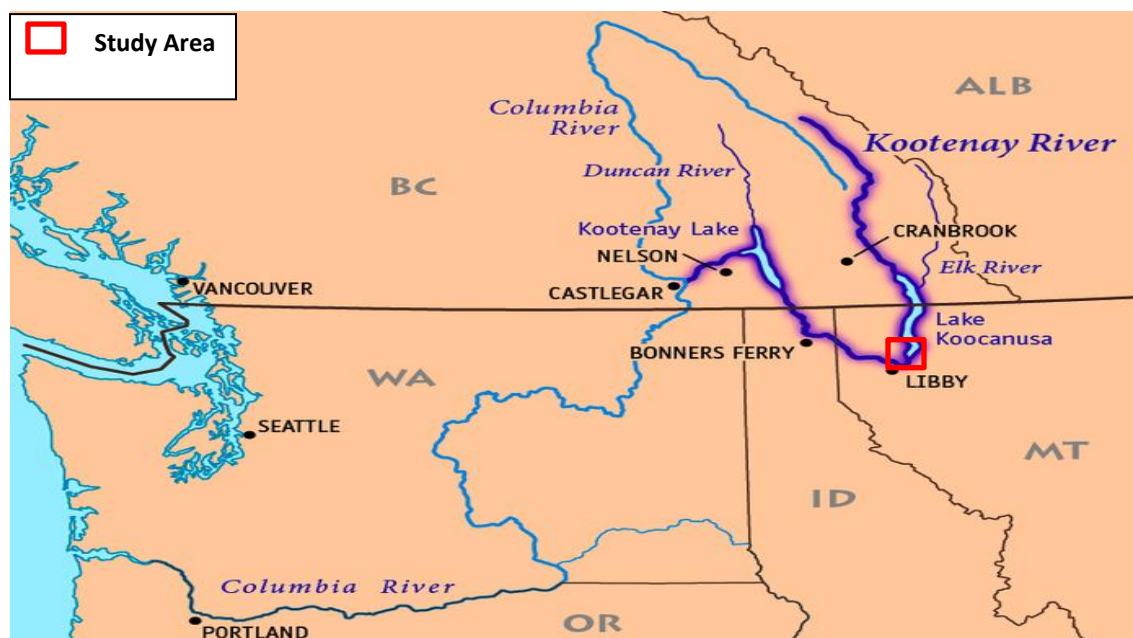


Figure 31. Map of the Kootenai River system (USGS & Digital Chart of the World, 2007).

The study area along the Kootenai is near Bonners Ferry, Idaho, and is a well-controlled section of river. Due to the slope and rainfall amount in the region, the Kootenai is under river management practices, with seven dams controlling seasonal flooding and providing hydroelectric power for the region (Figure 32).



*Figure 32.* Map of the management system for the Kootenai River. Courtesy U.S. Army Corps of Engineers. (“The High-Stakes Math Behind the West's Greatest River,” 2013)

The advantages of this river system are the fact that, since it is such a controlled system, the availability of ground truth data to be drawn from was immense as well as the fact that the system’s glacial origins provide for a very complex, braided system to develop and test processes and methods (Figure 33).



*Figure 33.* Photo taken by Offthetrail near Bonners Ferry, Idaho ( $48^{\circ} 41' 44.03'' N$ ,  $116^{\circ} 12' 21.96'' W$ ), overlooking the Kootenai River.  
<http://www.panoramio.com/photo/78403298>

The Belize River was chosen because it is a completely different type of fluvial system than the Kootenai River. The Belize River is fed from a binational watershed that reaches from the Peten district in Guatemala to the Caribbean Sea on the east coast of Belize (Karper & Boles, 2004). These major rivers drain the larger watershed that feeds the Belize River to include the Mopan, Hulmul, Chiquibul, and Salisipuedes (Karper & Boles, 2004) (Figure 34).

The focus of this study will be on the lower reaches of the Belize River, which contains meandering bends due to the gentle slope of the coastal regions. This provides a stark contrast to the Kootenai River system and provides a rigorous testing location for the tools, methods, and conclusions drawn in this study (Figure 35).



*Figure 34. Map of the Belize River study area (“School Assemblies and Marine Science Presentations by the Ocean Adventure”).*



© All Rights Reserved by Ceiba Realty Belize



*Figure 35.* Photo taken by Ceiba Realty Belize ( $17^{\circ} 31' 49.06''$  N,  $88^{\circ} 19' 6.26''$  W) overlooking the Belize River, <http://www.panoramio.com/photo/10780038>.

### *Software*

The software utilized in constructing the various components of the decision system frame work can be found in Table 2. The software chosen for the framework was from a cost and availability stand point. However, there are various other GIS and BN softwares that could be used in a similar configuration to achieve the same goal of a decision system. (see Appendixes A and B).

Table 2

*Decision System Component Software and Reference Link for Additional Information*

Software	Reference
Environmental Sciences Research Institute (ESRI)	<a href="http://www.esri.com/">http://www.esri.com/</a>
Norsys Netica	<a href="http://www.norsys.com/netica.html">http://www.norsys.com/netica.html</a>
ET Geowizard	<a href="http://www.ian-ko.com/">http://www.ian-ko.com/</a>
Riverine Bathymetric Toolkit (RBT)	<a href="http://essa.com/tools/rbt/">http://essa.com/tools/rbt/</a>
Python v2.6	<a href="http://www.python.org/">http://www.python.org/</a>

Note. There are several commercial companies that provide some feature extraction software; however, due to cost and research goals, ArcGIS was chosen as the core GIS software with any required development done through model builder and python, a scripting language.

*Data*

Both Kootenai and Belize river systems utilized remotely-sensed satellite imagery and in situ measurements as means for ingest into the spatial preprocessing component of the framework. Access to topographic data for the Kootenai River did allow for more analytics and comparison techniques, which will be discussed in the results and validation/verification sections (Tables 3 and 4).

Table 3

*Kootenai River Data Sources*


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Satellite Imagery	Digital Globe's Quickbird 2
	Multispectral and Panchromatic Sensors
	Collected on August 26, 2012
	Radiometric resolution of 16 bits
National Park Service (NPS) Topographic Point Data	<a href="http://gis1.idl.idaho.gov/Gis%20Website/index.shtml">http://gis1.idl.idaho.gov/Gis%20Website/index.shtml</a>
Airborne Imagery Derived River Currents	Infrared Image
	Collected on August 26, 2012
	Information regarding this technique can be found in the Airborne Infrared Remote Sensing of Riverine Currents published in the IEEE Transactions on Geoscience and Remote Sensing (Dugan, Anderson, Piotrowski, & Zuckerman, 2013).
	<a href="http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&amp;arnumber=6587783&amp;isnumber=4358825">http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&amp;arnumber=6587783&amp;isnumber=4358825</a>

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Table 4

*Belize River Data Sources*


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Satellite Imagery	GeoEye's Ikonos
	Multispectral and Panchromatic Sensors
	Collected on March 12, 2010
	Radiometric resolution of 16 bits
RiverRay ADCP River Currents	River discharge and velocity data collected with the RiverRay Acoustic Doppler Current Profiler (ADCP). RiverRay is a sensor produced by Teledyne RDI. ("RiverRay ADCP.", 2013)

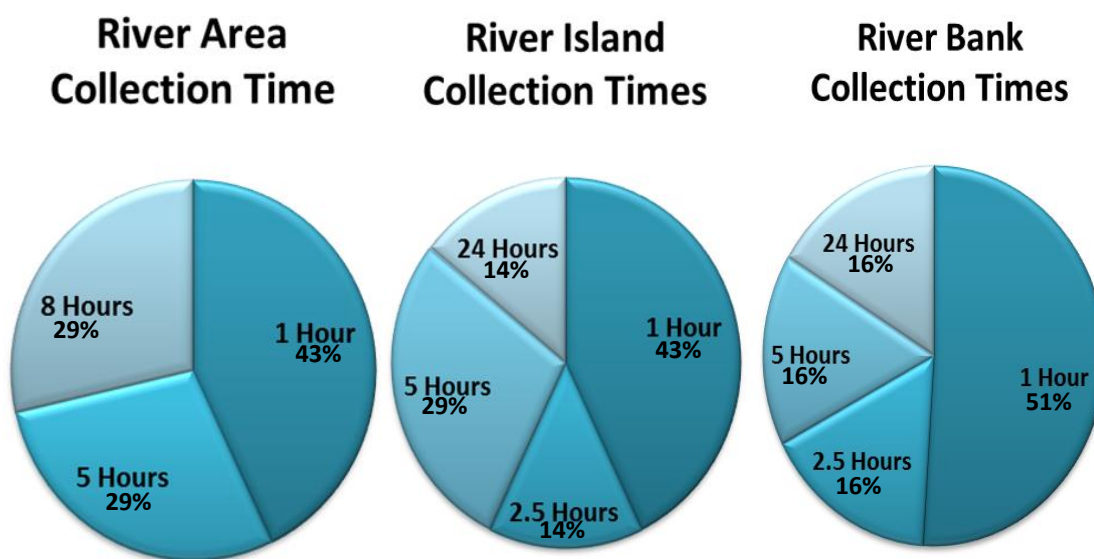
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## CHAPTER III

### FRAMEWORK RESULTS

#### Spatial Preprocessing

Applying the methodologies discussed in Chapter II to sections of the Kootenai River and Belize River probabilistic depth predictions were achieved. Normal process times for collecting the necessary river geomorphic features through on-screen digitizing could vary from hours to days. Figure 36 shows a small sampling of times obtained from riverine analysts estimating the collection time associated with each feature.



*Figure 36.* Pie charts of estimated times required to collect river features using conventional means. These values are qualitative in nature, as they are based off of estimates by subject matter experts. Environment, imagery, and geomorphology will always be unique and may skew these estimates. Survey conducted through [www.surveymonkey.com](http://www.surveymonkey.com).

Utilizing the semi-automated workflow through ArcGIS toolbox framework, process times were significantly reduced. River area, banks, centerline, and island areas were created using tools and procedures discussed in the methods section of the paper;

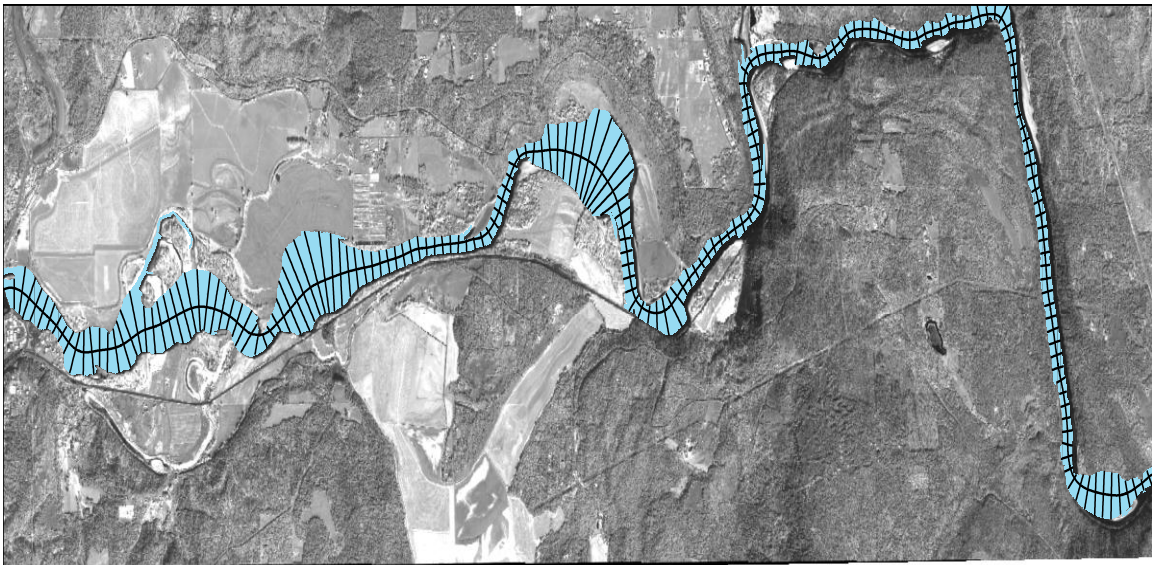


those times are represented by Table 5 and Table 6. A transect spacing of 100 m was chosen as the distance variable for both the Kootenai and Belize areas in the creation process (Figure 37 and 38).

Table 5

*GISc-derived variable's source, area measurement, and CPU processing time for the Kootenai River study area.*

Variable	Input Source	Area Measurement	CPU Time
River Area	NIR Image	3.23 sq. km	1:45
River Banks	River Area	51.2 km	0:02
Islands	River Area	1.24 sq. km	0:02
Centerline	River Banks	20.58 km	0:17
Transects	Center Line	206 cross sections	0:48

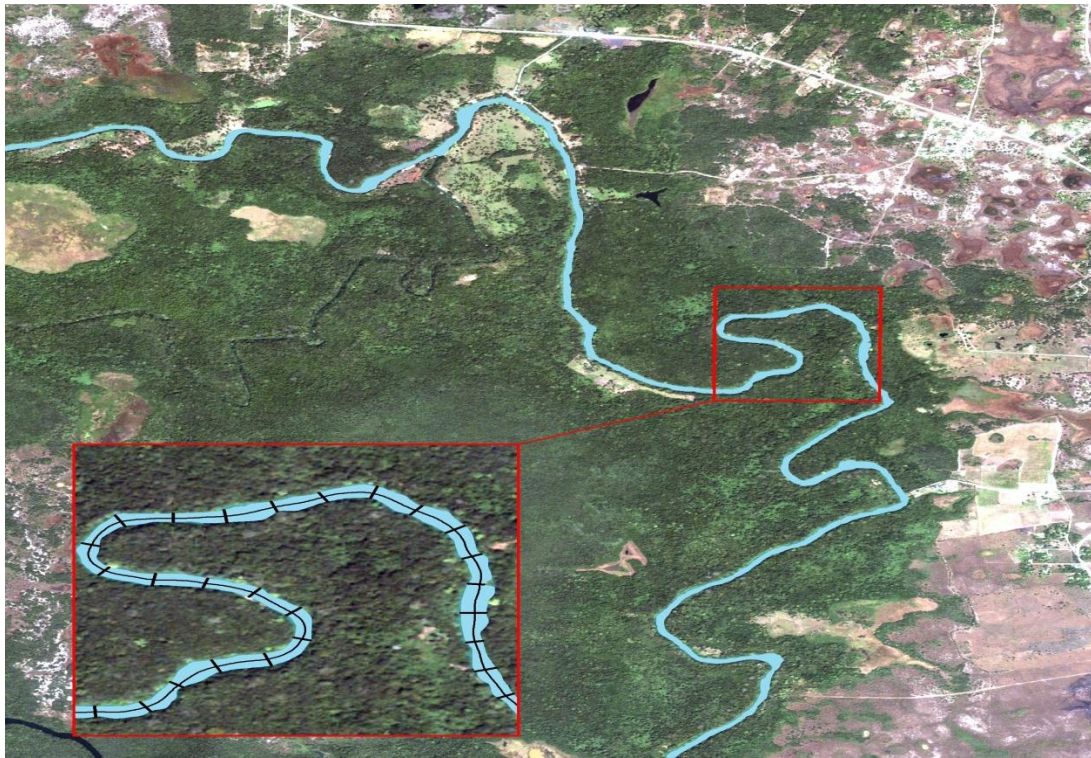


*Figure 37. Results of the contour centerline and transect creation for the Kootenai River. Evenly-spaced transects due to a geometrically accurate centerline provide a better estimate of river width for the BN to conduct a prediction execution upon. The Kootenai image displayed is a Quickbird 2 multispectral NIR band collected on August 26, 2010.*

Table 6

*GISc-derived variable's source, area measurement, and CPU processing time for the Belize River study area.*

Variable	Input Source	Area Measurement	Process Time
River Area	NIR Image	1.34 sq. km	0:48
River Banks	River Area	68.75 km	0:03
Islands	River Area	N/A	N/A
Centerline	River Banks	33.62 km	0:18
Transects	Center Line	338 cross sections	0:51



*Figure 38. Map containing results of the contour centerline and transect creation for the Belize River. The Belize image displayed is a GeoEye NIR band collected on March 12, 2010.*

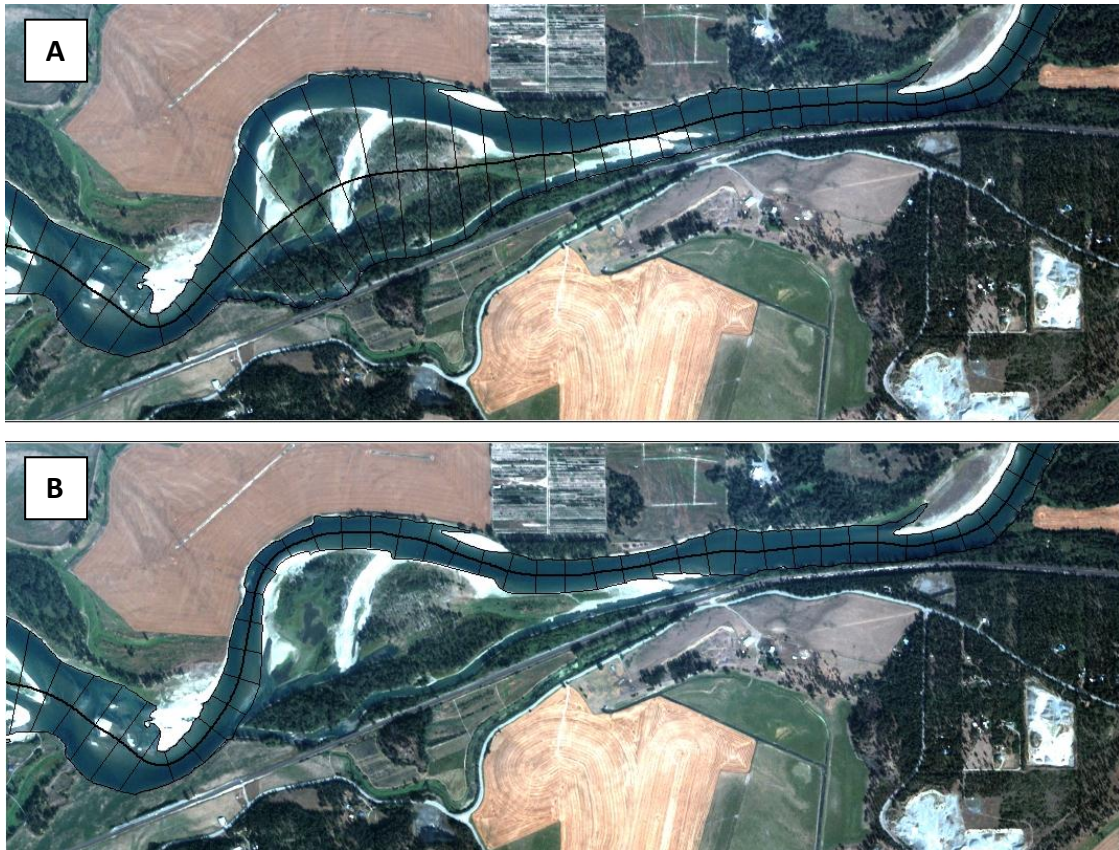
In comparison, Table 5 and Table 6 the process times are similar, although the Belize image area was significantly larger, producing longer banks and centerline features which resulted in more transects. This is due to the narrower, more simplistic geomorphologic form of the Belize River as compared to the more braided Kootenai River study area. The Central Processing Unit (CPU) times are highly dependent on the individual system or server resources and may vary. The total workflow process time for both areas was approximately 12 minutes based on an experienced user following an analytical process. The workflow time will vary based on analytical expertise and familiarity given that each river is unique; however, the processing time should remain similar as the tools and methods have been applied through a framework approach.

Utilizing the tool set and workflow management process, the probability engine is ready to execute a depth prediction in minutes versus hours. This reduction could provide a first-look approach at the river system, providing areas where further analysis may be required to come to an operational decision.

### Spectral Analysis

The relocation of the centerline can have a significant impact on several forcing condition calculations, such as sinuosity and radius of curvature. The most important impact is the effect on the transect creations themselves, as these features hold the wetted width attribute (Figure 39).





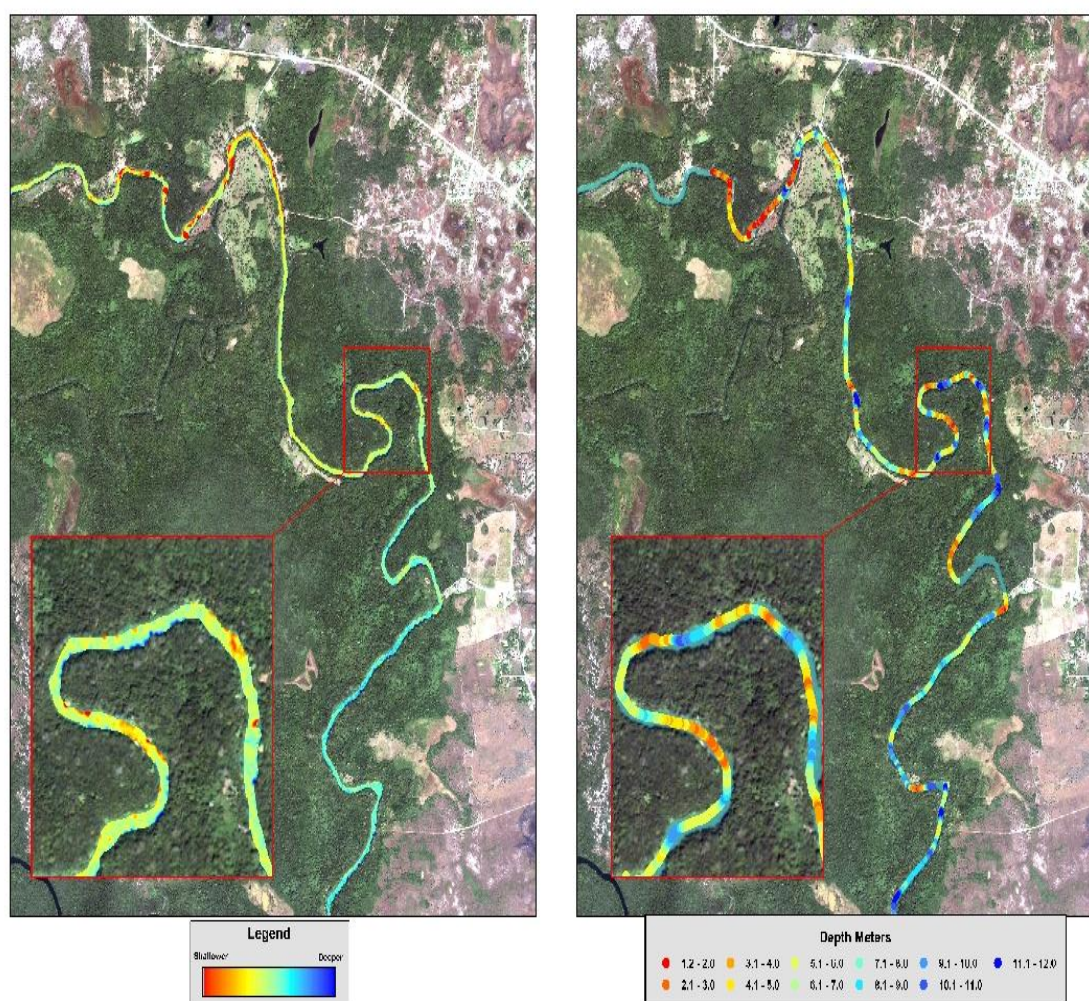
*Figure 39.* Comparison between centerline features before and after the red/green ratio analysis. Map A represents normal centerline and transects, while Map B shows the centerline shift due to the red/green ratio analysis. Transects created from this shift are significantly different than the top image.

Spectral characteristics should be taken into consideration when any band rationing technique is applied (Jensen, 2007). For instance, the ratio may produce a relatively shallow value near the bank which could have resulted from vegetative canopy shadowing (Figure 40). The spectral comparison between different portions of the spectrum to obtain information about a particular phenomenon is common place (Jensen, 2007). Although an automated workflow was created, significant research should be conducted to provide suitable conditions when this ratio technique could be automatically applied. Therefore, the decision of centerline transference to thalweg location still resides



an analytical function of the subject matter expert applying the red/green ratio as a guiding element to that placement.

### Red Green Ratio Comparison to Depth Values



*Figure 40.* Shadowing effect from vegetative cover. However, the general conclusion that the river is shallower in the northern-most section is easily obtained from the red/green ratio.

### BN Forcing Conditions

Executing the BN requires passing information from transects to the BN, which was performed with both regional and dynamically-calculated environmental constraints,

including a percentage of uncertainty associated with the constraint. Tables 7 and 8 show the variables contained within the transect feature class for both study areas before transferring the information to Netica.

Table 7

*Kootenai River Forcing Conditions Utilized in the BN Prediction Engine*

Variable	Value	Uncertainty	% Uncertainty
Width	*	*	2.5%
Sinuosity	1.449023	0.07245115	5%
Radius of Curvature	*	*	5%
Slope	0.0005	0.000025	5%
Discharge	220 cms	5.5 cms	2.5%
Velocity	*	*	2.5%
Drainage Area	32,867 sq. km	1643 sq. km	5%

Note: \* represents values that are variable per transect the other values are applied to all transects.

Table 8

*Belize River Forcing Conditions Utilized in the BN Prediction Engine; Higher Uncertainty Values Are a Result of a Lack of Ground Truth Data.*

Variable	Value	Uncertainty	% Uncertainty
Width	*	*	10%
Sinuosity	2.234428	0.335164	15%
Radius of Curvature	*	*	15%
Slope	0.00025	0.000038	15%
Discharge	75 cms	11.25 cms	15%
Velocity	*	*	15%
Drainage Area	6,000 sq. km	900 sq. km	5%

### Bayesian Network

The predictions returned from Netica through python are rendered in ArcMap as a point feature class representing the center x, y location of the original transect. The probability features hold several original attributes from the transect, such as transect ID, x, y, and shape width, but also has several new attribute values of probability values and experience (Table 9). Experience is defined by how many times the network recognized the variable combination in the prediction; however, this number needs further research into how it applies to a qualifier of prediction.

Table 9

*Example of a Probability Prediction Output from Netica as an Attribute Table in ArcGIS.*

trans_id	prob_atlea st_0pt5m	prob_atlea st_1m	prob_atlea st_2m	prob_atlea st_3m	prob_atlea st_4m	experience
0	1	0.996287	0.586631	0.174723	0.070663	1069.83
1	0.970557	0.888473	0.532876	0.445130	0.343033	0.0001
2	0.970741	0.928288	0.346945	0.201766	0.157860	83.0001
3	1	0.999833	0.790635	0.286990	0.107745	3689.075
4	1	0.996342	0.667932	0.189849	0.065985	780
5	1	0.992420	0.518415	0.080709	0.021157	780
6	1	0.962116	0.759866	0.298180	0.097267	100
7	1	0.999357	0.710737	0.173624	0.041496	3689.075
8	1	0.993555	0.560626	0.138331	0.053162	-9999
9	0.968268	0.936536	0.376817	0.263475	0.126928	-9999
10	1	0.999988	0.889930	0.599599	0.304244	-9999
11	0.955821	0.911641	0.665408	0.621108	0.576880	-9999
12	1	0.923998	0.748690	0.185369	0.000060	-9999
13	0.969072	0.938144	0.607602	0.477392	0.405189	-9999

Note: Not all attribute values are represented in this table.

### Cartographic Representation

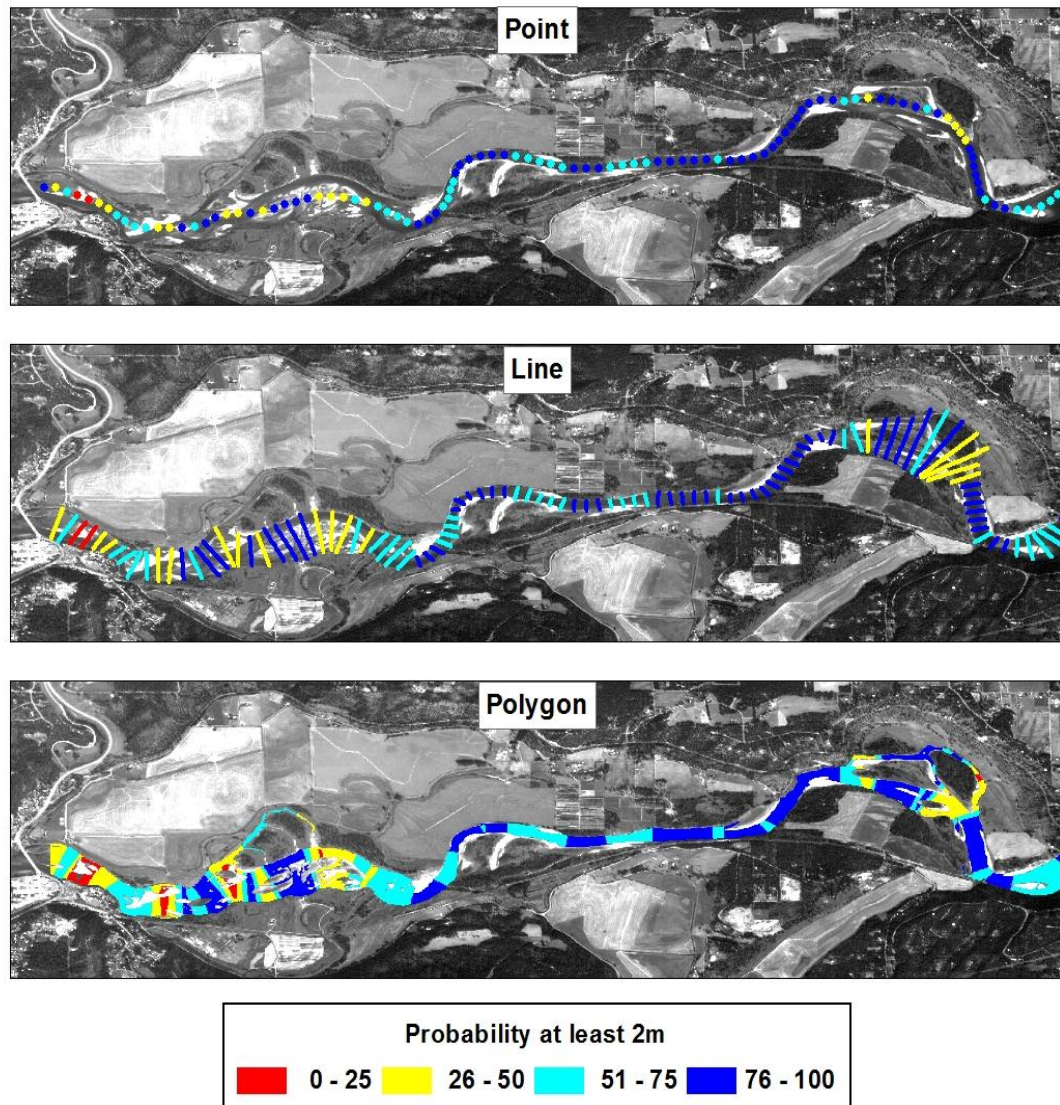
The cartographic processing steps described in this section apply to this study area. However, every river system is unique, and there will be an instance where points would better serve the purpose of displaying the probability predictions. Scale is another determining factor. If the product is a small scale (such as 1:10,000), then polygons would provide the best results, but if the product was large scale (such as 1:50,000), then points would provide just as much information as the polygons.

The manner in which the prediction information will be viewed is another determining factor, as there is a significant difference in a .jpeg representation and a dynamic viewer such as Google Earth. Points, lines, and polygons can all be used to convey information all three geometry types have positives and negatives the situation, scale and viewer will drive which one is the best to convey the probability information.

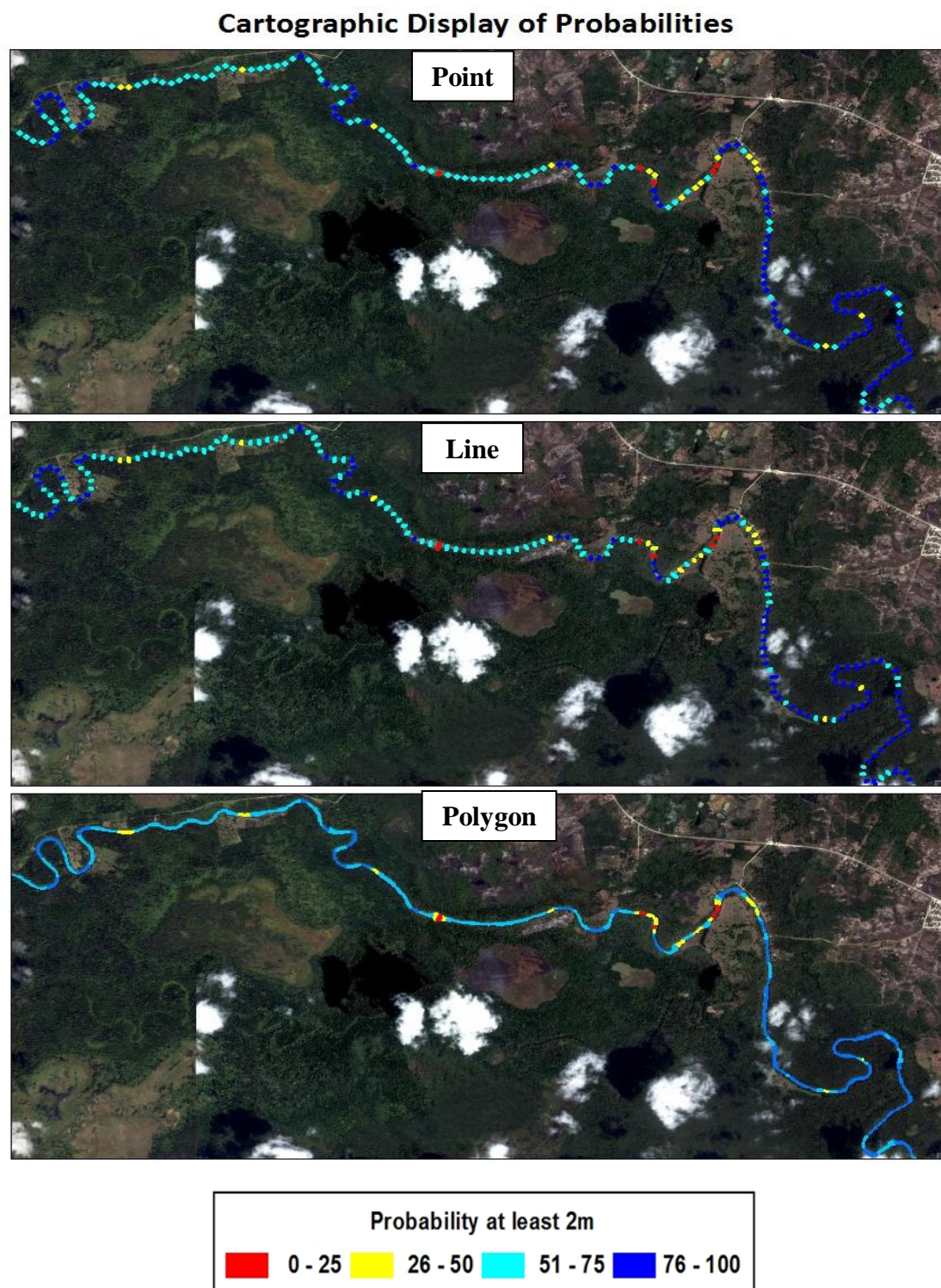
For the Kootenai area, polygon geometry was the best possible cartographic solution due to scale (Figure 41), while probabilities points would be the best choice for the Belize due to both scale and deliverance of information (Figure 41).



## Cartographic Displays of Probabilities



*Figure 41.* Point, line, and polygon cartographic display comparisons for the Kootenai River. Polygons provide the most information to make an informed decision from due to the scale and complexity of the fluvial system.



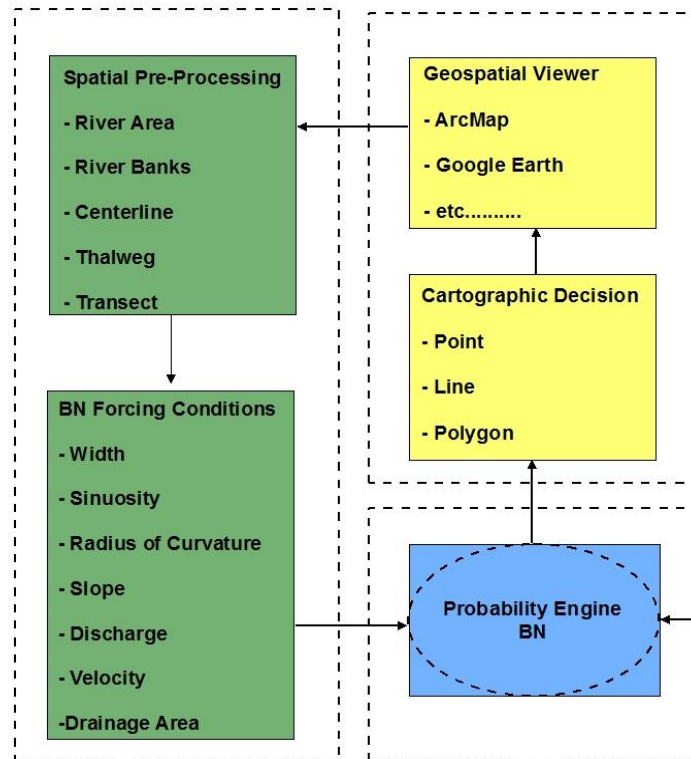
*Figure 42.* Point, line, and polygon cartographic display comparisons for the Belize River. Points provide the most information to make an informed decision from due to the scale and complexity of the fluvial system.



Every river is unique and may require a combination of these techniques to best display the probability prediction information to answer the spatial question that is being addressed.

### Framework

The previous sections have all pertained to the individual components of the decision framework and what information was obtained from each. The focus of this research was constructing those elements into a framework in which informed decision-making can occur, and therefore is the true result of this study (Figure 43).



*Figure 43.* The decision framework functioning as one workflow to produce decision aids.

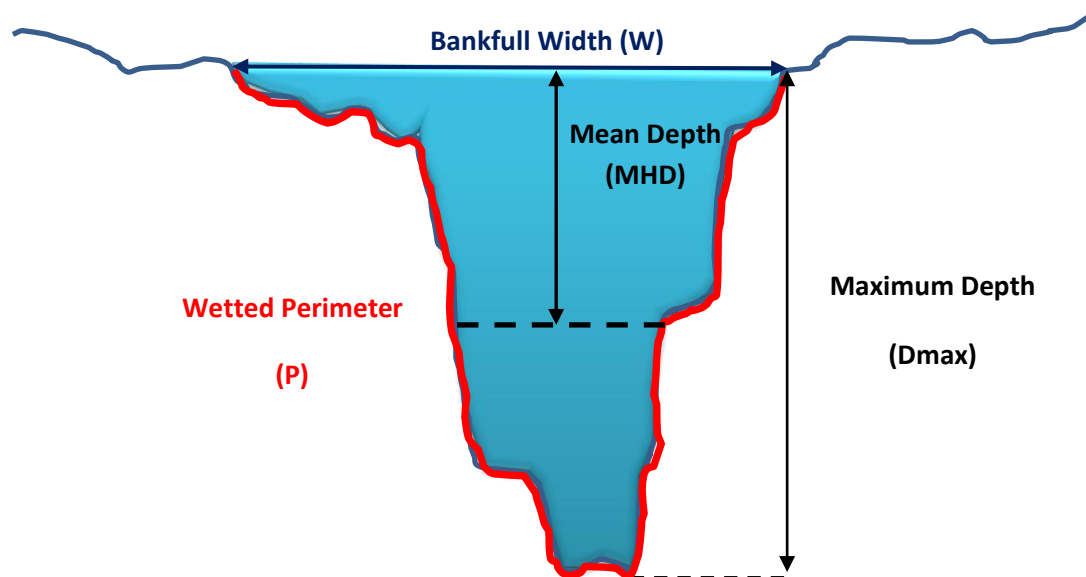
## CHAPTER IV

### VALIDATION AND VERIFICATION

Validating the results and accuracy of the BN was not a goal of this study, however some comparison methods had to be applied to ensure that the framework was functioning as designed. A measure of mean hydraulic depth (MHD) was used as a comparison statistic to measure the BN performance.

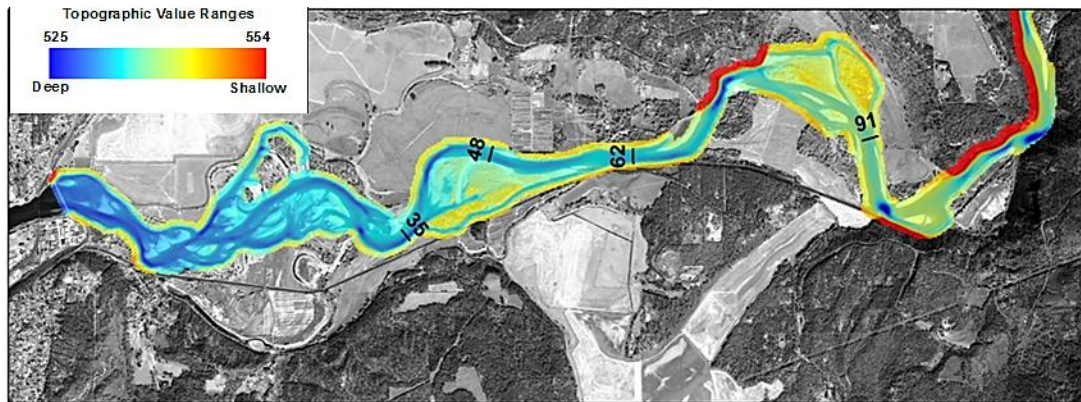
#### Mean Hydraulic Depth

MHD is defined as the average water depth between river banks. The relationship between wetted area and MHD is characterized in Figure 44. The wetted perimeter value is contained within the transect geometry that was derived from the centerline feature. MHD is calculated by finding the depth at points along the transect between the banks and dividing it by the number of stations (McKean et al., 2009). Three different sampling methods for calculating the MHD were examined to find the most efficient method.



*Figure 44.* The relationship between Wetted Perimeter, Bankfull Width, Maximum Depth as it relates to the Mean Depth.

Before applying any of the MHD methods to the National Park Service (NPS), topographic points that contain the water depth values used to calculate MHD. An interpolation was performed turning the point data into a surface using the ArcGIS tool topo to raster with a bilinear calculation and extracted to only include the river portions. This step was necessary to insure a valid comparison and to aid in calculation and processing speeds (Figure 45).



*Figure 45.* Interpolated topographic data displayed as a colored surface. MHD was only calculated for the Kootenai River by analyzing transects cross sections against NPS topographic elevation data.

### MHD Calculation

The first method was to apply a mathematical calculation inside ArcGIS for each transect. However, further processing of the transects was required to insure a defined sampling interval. This was achieved through the ArcGIS tool densify where a value of 10 m was applied. This ensured that the transect line feature would have vertices at a 10 m interval. The line vertices were transformed into a point feature class through the feature vertices to points tool, where all vertices were selected. The sample tool utilized these vertices to obtain elevation values from the topographic surface.

Displaying the tabular results from the sampling in geographic space allowed for the spatial join function to join the sample locations with the original transect geometry

from which they originated. Through this process, additional fields were added and calculated to include a sample minimum, maximum, and mean values. An MHD was obtained through the calculation of the samples maximum value minus the mean value (Equation 6).

$$S_{max} - S_{mean} = MHD$$

*Equation 6.* Sampling method calculation of Mean Hydraulic Depth (MHD).

Second method of creating MHD was the execution of zonal statistics functions inside ArcGIS's spatial analysis toolset. Similar to the sampling method, this tool takes transect locations and analyzes them directly to the topographic data allowing for calculations of minimum, maximum, and mean statistics. Comparing the results from the zonal statistics and the sampling method no statistically significant difference was found.

The third method was exploring commercial tools for calculating geomorphic datasets and hydraulic values. River Bathymetry Toolkit (RBT) was downloaded for evaluation from <http://essa.com/tools/rbt/download/>. The U.S. Forest Service, Rocky Mountain Research Station, Boise, Idaho, contracted ESSA Technologies, Ltd., to develop and maintain RBT. This kit already contained a suite of tools designed to interpret high-resolution Digital Elevation Models (DEMs) of river channels (McKean et al., 2009). Currently, RBT has tools for calculating the bankfull polygon and centerline and for cutting cross sections through the channel to extract hydraulic parameters such as wetted area, bankfull width, hydraulic radius, and MHD (McKean et al., 2009). Other geomorphic calculations have been added to the toolkit for stream gradient and sinuosity (McKean et al., 2009). Importing transects into RBT allowed for the MHD to be calculated for each cross section.

Through the employment of sampling, zonal statistics, and RBT, there was no significant difference between MHD values. However, further comparative testing should be performed to provide a full analysis of the differences to draw a more definitive conclusion. For this study, the MHD variable was of interest for comparing the probability prediction to a value. Therefore, the RBT method was chosen because calculation methods produced similar values for MHD and the RBT's inherent transect profiling capability.

### Comparison Techniques

Once MHD had been calculated for each transect, a comparison was drawn between MHD and the probability of being at least 2 m depth. For this study, the 2 m depth was chosen because river navigation is the decision systems main goal. Three methods were selected to give some sense to the validity of the data being returned from the BN and undergoing cartographic processing for information convince.

The first selects transects that had an MHD of at least 1.8 m. Of those transects, an additional selection was created that only contained transects with a greater than 70% probability of being at least 2 m (Table 10, Method A).

The second approach selected transects that had an MHD of at least 1.8 m and were continuous from the left bank to the right bank. Of those transects, an additional selection was created that only contained transects with a greater than 70% probability of being at least 2 m (Table 10, Method B).

The third method selected transects that had an MHD of at least 1.8 m and only had in situ velocity constraint information. Of those transects, an additional selection was

created that only contained transects with a greater than 70% probability of being at least 2 m (Table 10, Method C).

Table 10

*Prediction Results of the Three Transect Comparison Methods*

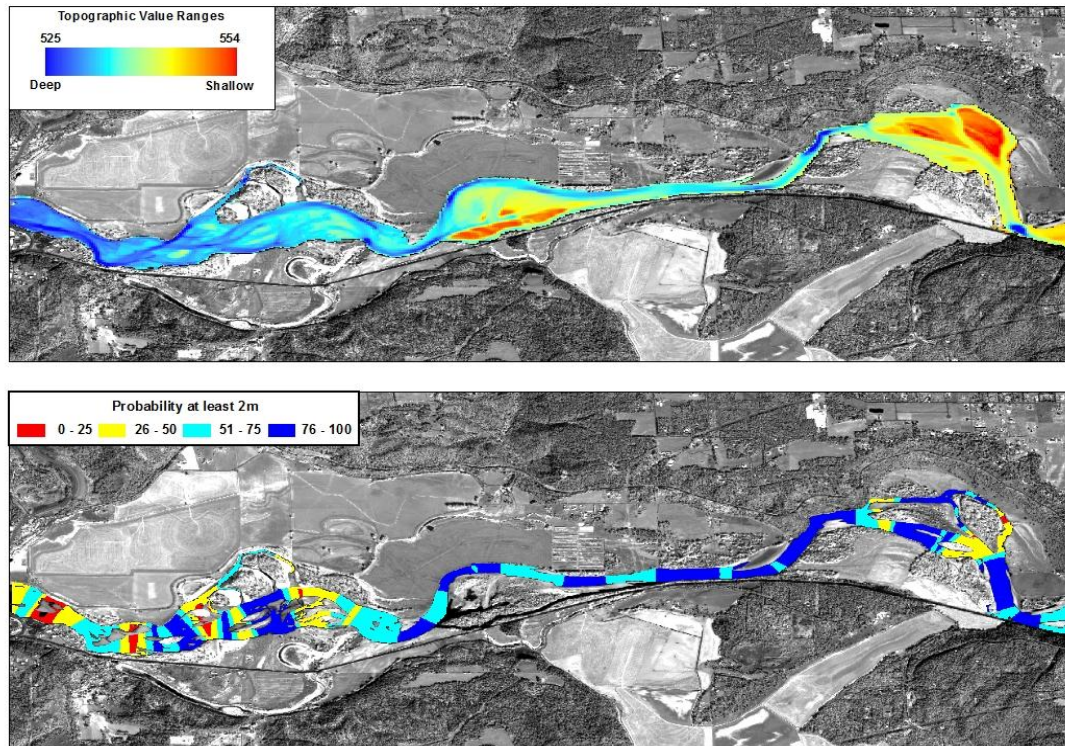
<b>Transect Constraints</b>	<b>Method A</b>	<b>Method B</b>	<b>Method C</b>
Mean Hydraulic Depth > 1.8 m	55	50	11
Probability > .70	46	44	10
Correctly Predicted	84%	88%	91%

Note: Results presented in this table do not have any island areas removed from the width variable.

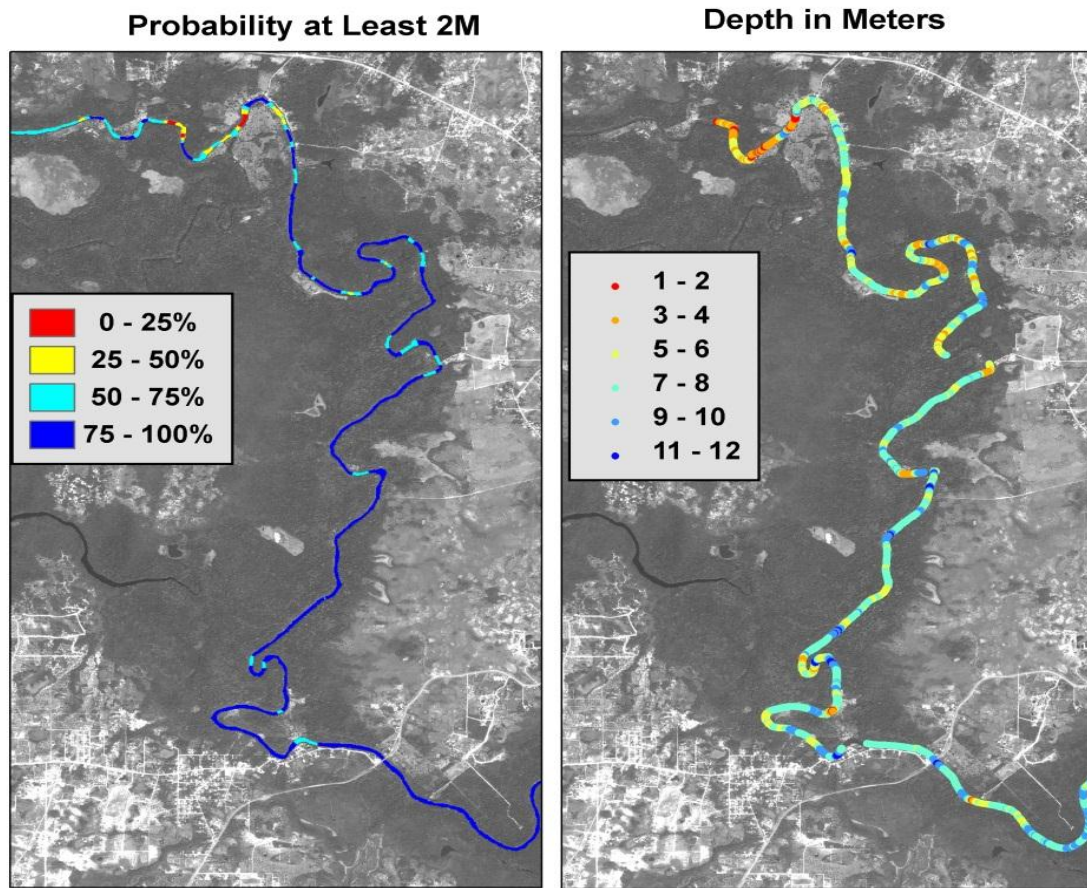
Table 10 contains results for a small section of the Kootenai River and should not be extrapolated to other river systems or used as a true quantifier for the predictability of the BN. There are other studies and papers that are more focused on this issue. For more information regarding the BN accuracy and performance, refer to work on river velocities using a BN conducted by Palmsten et al. (2013). Due to the lack of reliable bathymetric data, a quantitative prediction result was not conducted on the Belize River. However, the qualitative results are shown in cartographic comparisons for both the Kootenai and Belize study areas (Figures 46 and 47).



### Probability Comparison to Topographic Data



*Figure 46.* Comparison between probability results and topographic data. The topographic data does not display actual depth values. However, it does show the spatial relationship of deeper and shallower areas compared to the probability question of at least 2 m depth.



*Figure 47.* Comparison between probability prediction and ADCP bathymetric data. The area in the northern most portion of the river is the shallowest which the prediction clearly indicates.

The sensor used on the Belize River for data collection only measured point measurements along the thalweg location, therefore direct comparisons between the predicted depth probability and the MHD would not have yielded an accurate result. However, the general characteristics of the river system express a qualitative spatial correlation; those areas are best expressed where the river measurements indicate the shallowest depths. This is due in part to the cartographic display of the probability map indicating the probabilities of at least 2 m, and would therefore tend to display the

shallower areas more distinctly as that is the spatial question being addressed for safety of navigation concerns.

## CHAPTER V

### DISCUSSION

#### Transect Modification

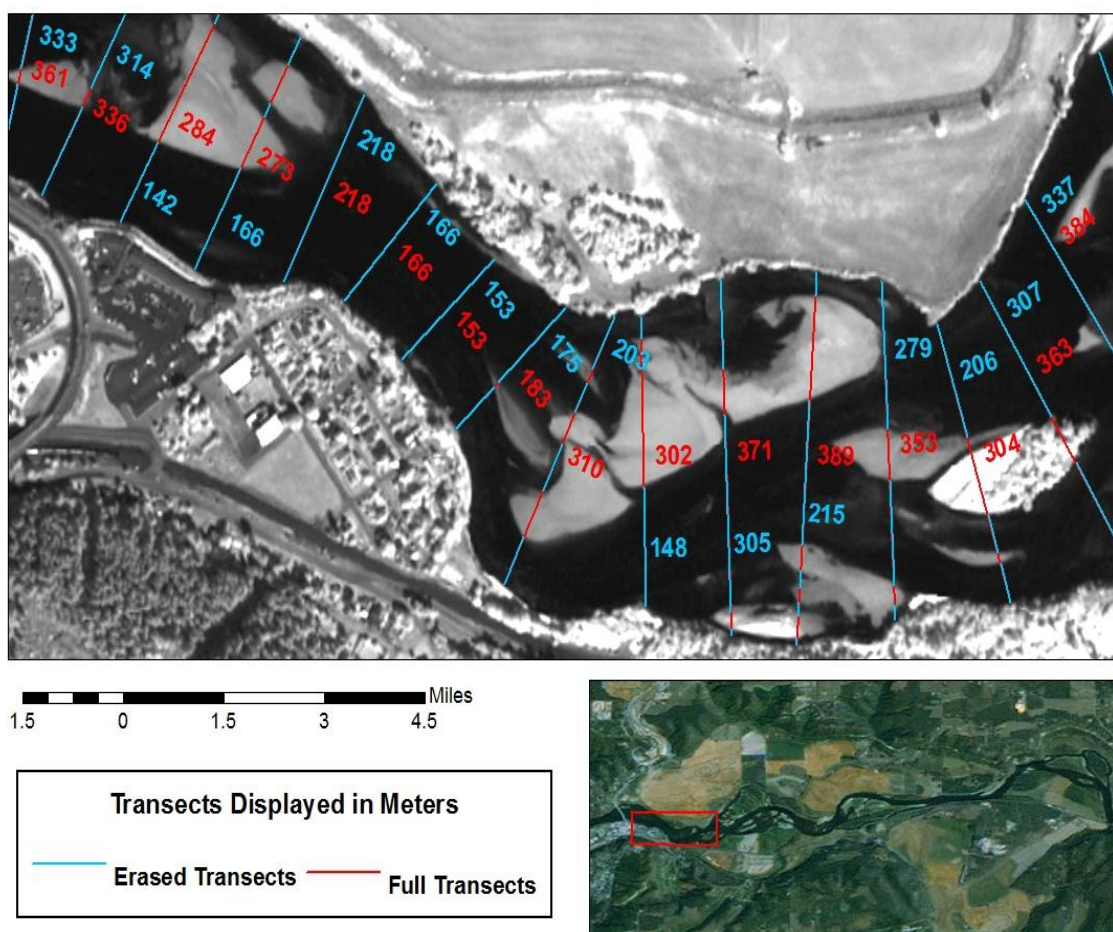
The transect width is one of the main observables that we can derive from imagery; however, it may contain a misleading value that does not approximate the true wetted width of that specific transect if island areas are present (Smith & Pavelsky, 2008). The removal of the section of transect present on land results in a new width variable for the BN to apply for prediction (Figure 48).

A transect width adjustment tool was developed to solve this issue by taking transects that spatially intersect the island feature class and erasing those areas from the original transects. The new geometry width can be calculated and stored within the hydraulic width column.

Although the island extraction process is a spatially valid one, it does impact the river width variable which is the single most influential prediction variable in the BN (Figure 48). Partial testing revealed that continued research would be needed to apply constraint propagation of the other physical parameters such as discharge and velocity. Any propagation of constraint values would have to take into consideration the thalweg location prior to distribution of values among the segmented transect lines. This would inherently treat all those line segments now as individual transects increasing the number of predictions (Figure 48).



### Width Comparison Between Transect Methods



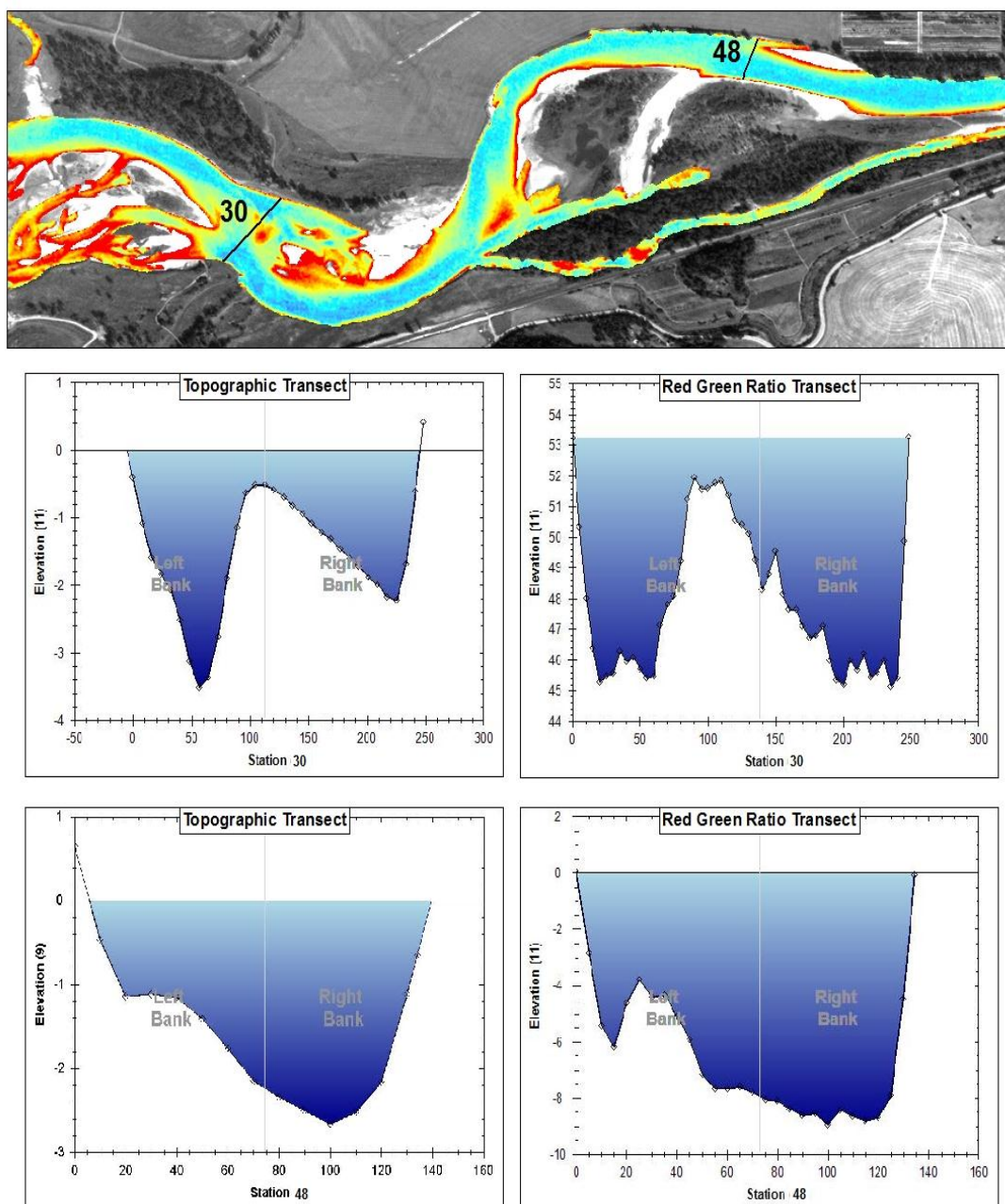
*Figure 48.* Spatial relationship between erased and full transects that have been spatially altered due to the presence of island areas. Main image is the NIR band. The locator is a map service published by ESRI Source: ERSI, i-cubed, USDA, USGS, AEX, GeoEye, Getmapping, Aerogrid, IGN, IGP, and the GIS User Community.

### Mean Hydraulic Depth

The MHD was used only as a qualifier for how well the BN performed in predicting depth. MHD alone is not a reliable predictor for the navigability question of the river as, by definition, it ignores the river bottom shape entirely (Figure 49). However, comparing the red/green ratio directly to the topographic data utilizing the RBT provides insight into the bottom shape. Coupling MHD with the band ratio

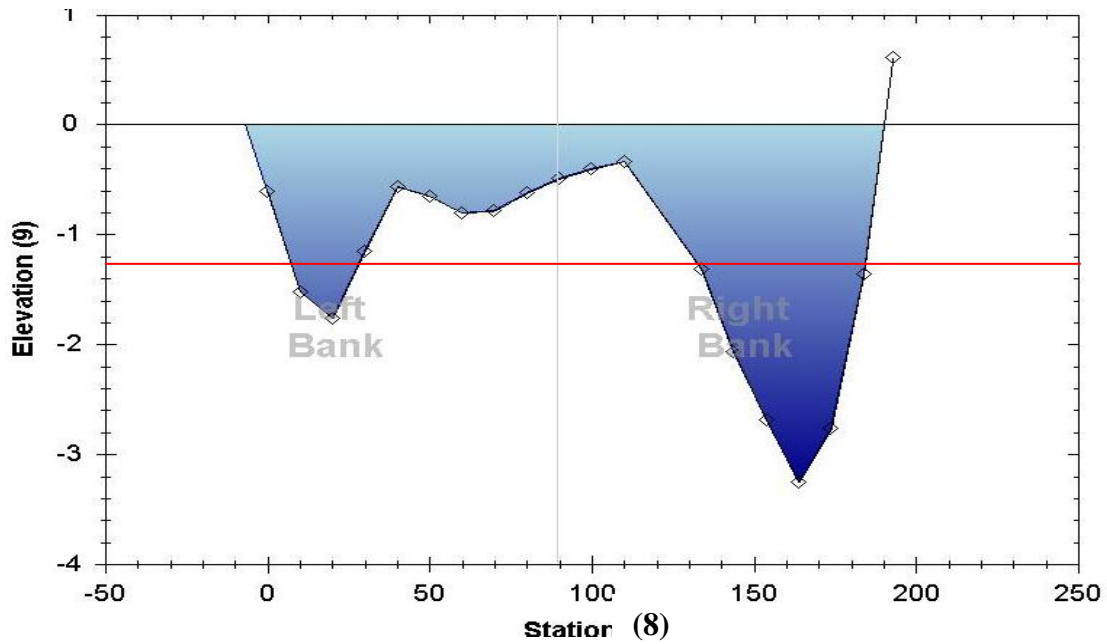
technique provides information that can be used by a subject matter expert as to where and with what confidence the most likely location of the deepest portion of the river is for navigational safety (Figures 49, 50, and 51).

### Red Green Ratio Transect Comparison to Topographic Values



*Figure 49.* Bottom shape of the topographic transects as it relates to the shape derived from the red/green ratio profile plots generated by RBT. RBT is designed to ingest topographic data not a band ratio value ranging from 0-1 however, the graphing functions

of RBT allow for direct comparisons of select transects. The ratio shape is more detailed due a much higher pixel resolution than the interpolated topographic dataset. The X axis represents the transect distance value the Y value marked as elevation is a correct depth for the topographic transect plots but is not a representation of the depth for the ratio values. The main intent is to examine bottom shape not a quantitative depth value.



*Figure 50.* Transect 8 bottom shape where the red line represents the MHD of -1.3 m. Max depth vs. MHD as it refers to the navigability question.

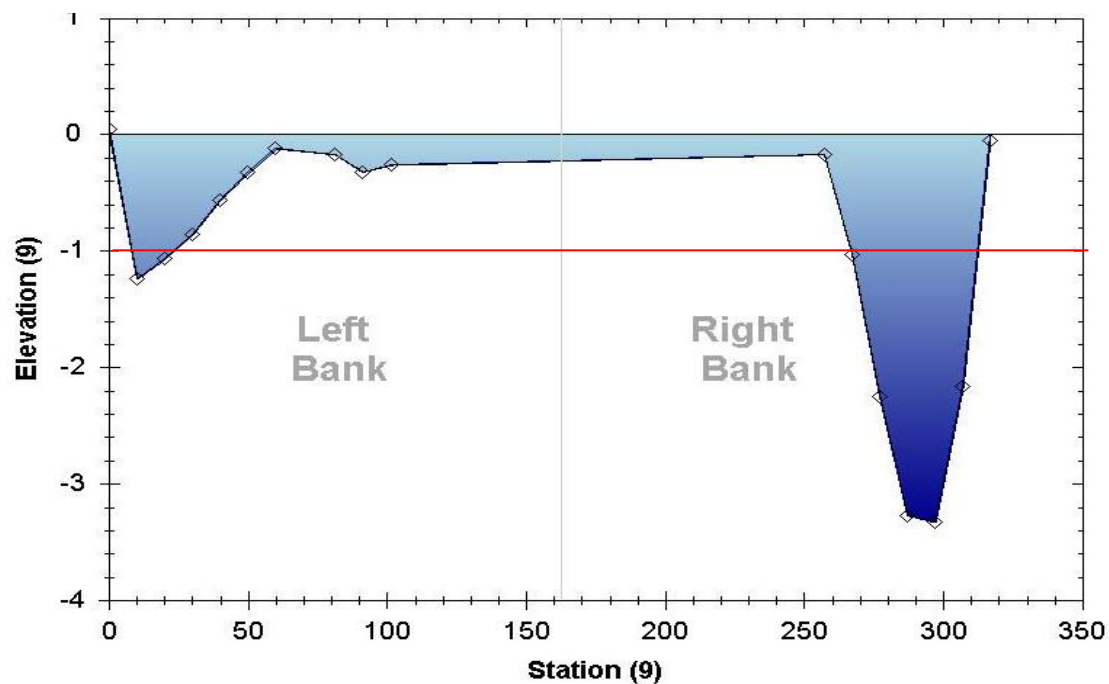


Figure 51. Transect 9 bottom shape where the red line represents the MHD of -1 m. Max depth vs. MHD as it refers to the navigability question.



### Future Work

Continued research of the methods and techniques mentioned in this section should yield a more spatially accurate result that allows for better and more detailed decisions, and therefore warrants further examination.

- Automated thalweg location methods and tools to support application of the band ratio technique including centerline relocation to the thalweg.
- Transect modification methods of redistributing environmental forcing conditions of velocity, discharge, and slope to new transect segments when island areas are present.
- Tools and processes for calculating slope and drainage area from DEMs should be investigated. The RBT already has this capability and should also be considered when deriving information from DEMs.
- Exploring a new version of Netica that is initially referred to as GeoNetica. It is supposed to inherently incorporate the spatial component and may prove as a way to simplify the framework.

## CHAPTER VI

### CONCLUSION

Environmental scientists are increasingly recognizing the impact that uncertainties from various sources or processes can have on the results and conclusions drawn through the spatial analytical process (Maguire et al., 2005). This study has also shown the need for more probabilistic modeling to take place inside the environmental science community, since all data feeds are only a representation of reality and are therefore probabilistic in nature.

The benefits of a BN in regards to environmental conditions and relationships are apparent, but when applied in a controlled environment within a decision framework, the impact on decision making is profound, as this study has proven. The ability to include uncertain or unavailable input variables coupled with expert knowledge about those variables makes BNs a very powerful tool in decision support systems (Plant & Holland, 2011)

There are three main benefits to using BNs as a representation device that is meant to organize knowledge about a particular condition (Darwiche, 2009). First, BN's are a richer model for environmental studies than a deterministic model because it can have more parameters that interact directly and indirectly (Maguire et al., 2005). Second, BNs describe relationships of causes and effects using a graphical framework that provides for quantification of probabilities and clear communication of the results (Fenton & Neil, 2007). This modularity is best using the directed acyclic graph (DAG), which in itself is consistent with what most people are accustomed to in the GIS community due to the similarity of the DAG with the model builder framework inside

ArcGIS. Third, BNs perform computationally fast uncertainty assessments in complex, multidimensional systems, and therefore are ideally suited for GIS modeling (Maguire et al., 2005).

This study has demonstrated the usefulness of integrating Geography and BNs in a loosely coupled architecture. This coupling of GISc and BNs allows for the creation of a decision system framework for spatial analytics, probabilistic execution, and information conveyance. Building the decision framework to be flexible, but include component tools and methods that lock in spatial sciences for collecting information, establishing relationships of variables and informational display cartographically, inherently provides the user the best possible decision-making aid.

Geography's traditional method of information transference through maps is the ideal means for delivering probabilistic spatial information. However, there must be a baseline of knowledge obtained by both the analyst and decision maker since as with most things GIS-related, there is a high risk instead of "garbage in garbage out you get garbage in and gold out" (Allan, 2013). All maps have a purpose and a message, both of which needs to be fully understood and considered before any decision-making process takes place.

## APPENDIX A

### GIS SOFTWARE

#### ***Commercial:***

- Autodesk – Products include Map 3D, Topobase, MapGuide, and other products that interface with its flagship AutoCAD software package.
- Bentley Systems – Products include Bentley Map, Bentley Map View, and other products that interface with its flagship MicroStation software package.
- ENVI - Utilized for image analysis, exploitation, and hyperspectral analysis.
- ERDAS IMAGINE by ERDAS Inc- Is used throughout the entire mapping community (GIS, Remote Sensing, Photogrammetry, and image compression).
- Esri – Products include ArcGIS, ArcSDE, ArcIMS, ArcWeb services, and ArcGIS Server.
- Intergraph – Products include G/Technology, GeoMedia, GeoMedia Professional, GeoMedia WebMap, and add-on products for industry sectors, as well as photogrammetry.
- MapInfo by Pitney Bowes – Products include MapInfo Professional and MapXtreme.
- Smallworld – developed in Cambridge, England, by Smallworld, Inc. and purchased by General Electric and used primarily by public utilities.

#### ***Open Source:***

- GRASS GIS – Originally developed by the U.S. Army Corps of Engineers, open source: a complete GIS
- SAGA GIS – System for Automated Geoscientific Analysis - a hybrid GIS software. SAGA has a unique Application Programming Interface (API) and a fast-growing set of geoscientific methods, bundled in exchangeable Module Libraries.
- Quantum GIS – QGIS is an Open Source GIS that run on Linux, Unix, Mac OSX, and Windows.
- MapWindow GIS – Free, open-source GIS desktop application and programming component.

- ILWIS – ILWIS (Integrated Land and Water Information System) integrates image, vector, and thematic data.
- uDig – Open-source GIS desktop application (API and source code (Java) available).
- gvSIG – Open-source GIS written in Java.
- JUMP GIS / OpenJUMP – (Open) Java Unified Mapping Platform

## APPENDIX B

### BELIEF NETWORK SOFTWARE

Information obtained from “Software: Bayesian Networks and Bayesian Classifiers” (2013).

#### ***Commercial:***

- AgenaRisk, visual tool combining Bayesian networks and statistical simulation
- Analytica, influence diagram-based, visual environment for creating and analyzing probabilistic models (Win/Mac).
- AT-Sigma Data Chopper, for analysis of databases and finding causal relationships.
- BayesiaLab, complete set of Bayesian network tools, including supervised and unsupervised learning and analysis toolbox.
- Bayes Server, advanced Bayesian network library and user interface. Supports classification, regression, segmentation, time series prediction, anomaly detection, and more. Free trial and walkthroughs available.
- Bayesware Discoverer 1.0, an automated modeling tool able to extract a Bayesian network from data by searching for the most probable model
- BNet includes BNet. Builder for rapidly creating Belief Networks entering information and getting results and BNet. EngineKit for incorporating Belief Network Technology in your applications.
- DXpress, Windows-based tool for building and compiling Bayes Networks.
- Flint, combines bayesian networks, certainty factors, and fuzzy logic within a logic programming rules-based environment.
- HUGIN, full suite of Bayesian Network reasoning tools
- Netica, bayesian network tools (Win 95/NT), demo available.
- Geo Netica, Bayesian network tool that handles spatial inputs and outputs.
- PrecisionTree, an add-in for Microsoft Excel for building decision trees and influence diagrams directly in the spreadsheet

#### ***Open Source:***

- BAYDA 1.0
- Bayesian belief network software (Win95/98/NT/2000), from J. Cheng, including *BN PowerConstructor*: An efficient system for learning BN structures and parameters from data. Constantly updated since 1997.

*BN PowerPredictor*: A data mining program for data modeling/classification/prediction. It extends BN PowerConstructor to BN based classifier learning.

- Bayesian Network tools in Java (BNJ), an open-source suite of Java tools for probabilistic learning and reasoning (Kansas State University KDD Lab)
- FDEP<sub>2</sub> induces functional dependencies from a given input relation. (GNU C).
- GeNIe, decision modeling environment implementing influence diagrams and Bayesian networks.
- JavaBayes
- jBNC, a Java toolkit for training, testing and applying Bayesian Network Classifiers.
- JNCC2, Naive Credal Classifier 2, an extension of Naive Bayes towards imprecise probabilities; it is designed to return robust classification, even on small and/or incomplete data sets.
- MSBN: Microsoft Belief Network Tools, tools for creation, assessment and evaluation of Bayesian belief networks. Free for non-commercial research users.
- PNL: Open Source Probabilistic Networks Library, a tool for working with graphical models, supporting directed and undirected models, discrete and continuous variables, various inference and learning algorithms.
- Pulcinella, tool for Propagating Uncertainty through Local Computations based on the Shenoy and Shafer framework.

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